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THE GROWTH AND PERFORMANCE OF ARTIFICIAL INTELLIGENCE IN ASSET MANAGEMENT

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ABSTRACT

We examine the growth and performance of AI-driven investing. Using investment advisers' regulatory disclosures, labor market data, and fund strategy descriptions, we document that AI-driven investing has grown steadily since the early 2010s and is concentrated among hedge funds. AI hedge funds outperformed non-AI hedge funds in the early years, but this outperformance declined over time, even among early adopters. Contrary to concerns about AI-driven strategy homogeneity, AI hedge funds exhibit lower return comovement than non-AI peers. Our findings highlight both the alpha-generating potential and the limitations of AI as a source of investment performance.

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1. Introduction

The active asset management industry constantly seeks new sources of performance, as the effectiveness of existing strategies often declines with scale and over time. In recent decades, Artificial Intelligence (AI) has emerged as a promising avenue in this search. By combining statistical techniques with big data, AI offers predictive power and self-adaptive capabilities that can guide investment decisions in evolving market conditions. Its potential to generate superior returns has attracted growing interest from both investment advisers and investors. Yet despite the development of AI-driven investing since the early 2000s and numerous anecdotal success stories, systematic academic evidence of its applications in asset management remains limited.[1]

In this paper, we systematically examine AI-driven investing in the U.S. asset management industry. The central challenge of our study is to identify where AI is deployed in investment decisions and to link this usage to fund characteristics and performance. We address this challenge through large-scale textual analyses of SEC-registered investment advisers' job postings, regulatory disclosures, and fund-level strategy descriptions. This large body of textual data reveals not only which investment advisers adopt AI, but also what purposes they use AI for and which individual funds apply AI-driven investment strategies. Our top-down approach allows us to make some progress in understanding the applications and alpha-generating ability of AI technologies in asset management.

We define AI-driven investing as a specialized subset of quantitative strategies that applies AI technologies for predictive modeling and trading signal generation. These include fully autonomous AI-driven strategies, as well as strategies in which AI signals directly inform

[1]Although investment advisers do not disclose their historical internal operations, multiple reports suggest that AI-driven investing has been used since well before 2000. For example, Renaissance Technologies reported that it "has been using machine learning as a means for trading for at least 30 years" (U.S. Senate Committee on Homeland Security and Governmental Affairs, 2024). Similarly, in 2018, a D.E. Shaw executive noted that "Over the past few decades we have developed and deployed increasingly sophisticated machine learning techniques."

investment decisions. Our definition therefore extends beyond the recent surge in generative AI and large language models (LLMs), which are typically used for research support and operational workflow. With this definition, our classification of investment advisers' regulatory disclosures shows that AI-driven investing has existed since at least the early 2010s. Although AI-driven strategies have steadily grown over the past decade, they remain a small niche within the quantitative strategy space.

Our analysis shows that AI-related job positions have grown rapidly in the asset management industry since the early 2010s — well before the recent surge in generative AI — and are particularly prevalent for hedge funds and less common for other investor types, such as mutual funds, venture capital funds, and private equity funds. Moreover, we identify AI-driven hedge funds ("AI funds") using archived strategy descriptions available at the prior year-end. We find that a large share of AI funds pursue systematic diversified macro strategies. As of 2024, 60% of AI funds in our sample fall into this category, which typically involves short-term trading in liquid instruments such as equity indices, commodities, fixed income, and currencies. Consistent with these strategies, AI funds offer relatively liquid shares to investors and exhibit significantly lower exposures to traditional equity risk factors.

To investigate whether these AI funds deliver superior performance, we analyze a large sample of 7,896 US hedge funds between 2006 and 2024. We find that AI funds outperform non-AI funds by approximately 6% annually on a benchmark-adjusted basis in earlier years. However, this outperformance decreases over time and becomes statistically indistinguishable from zero after 2017. The decline in relative performance cannot be explained by differences between early and late AI adopters, because even AI funds launched in the early years have lost most of their outperformance after 2017.

The relative performance of AI funds we document may reflect unobserved features of hedge fund advisers that use AI-driven strategies. To distinguish fund-level performance associated with AI-driven investing from these firm-level confounding forces, we further examine how AI funds perform relative to non-AI sibling funds managed by the same adviser. Our estimates show that AI funds outperform their sibling funds by 34.9 to 41.1 basis points per month, suggesting that our baseline results capture performance associated with AI-driven investing and are not solely driven by adviser-level heterogeneity.

Among policymakers, there has been a widespread concern that the use of autonomous AI algorithms may increase homogeneity and herding behaviors, which may amplify market vulnerabilities.[2] Contrary to these concerns, we find that AI funds exhibit lower return comovement than non-AI funds within the same strategy category. This finding suggests that AI funds trade on relatively diverse signals and do not necessarily represent a threat to market stability.

A driving force behind the growing scale of AI funds is investors' belief in AI's alpha-generating ability. To investigate these beliefs, we apply a revealed preference approach and analyze money flows into hedge funds. Our estimates demonstrate that AI funds did not receive inflows beyond what would be expected from their realized performance. They also suggest that mentioning AI in strategy descriptions per se does not attract investor flows, whereas the strong historical performance delivered by AI funds does.

This paper is closely related to a recent literature on the applications of AI and big data in asset management. Existing studies have developed novel proxies of AI adoption to assess its influence on investment performance. Bonelli and Foucault (2026) examine mutual fund stock-level investments and find that the performance of traditional fund managers declines after the stock is covered by satellite image data. Sheng, Sun, Yang, and Zhang (2025) infer hedge funds' use of generative AI from the association between 13F stock holdings and ChatGPT-generated signals. They show that institutions with a higher reliance on generative AI achieved better performance. In a similar spirit, Hu, Rohrer, and Zhang (2026)

[2]For example, see OECD Business and Finance Outlook 2021 "AI in Business and Finance" (Section 2.2) and US Homeland Security & Governmental Affairs 2024 Report "AI in the Real World: Hedge Funds' Use of Artificial Intelligence in Trading" (Section V.B.).

infer mutual fund AI strategies from the alignment between fund portfolios and machine learning-based trading signals. Using labor-based, institution-level measures of data science and AI adoption, Aragon, Kim, and Nanda (2025), Cen, Han, Han, and Jo (2025), and Zhang and Yuan (2025) also find evidence consistent with a positive impact of these technologies on investment performance.

We contribute to this literature by providing the first systematic analysis of AI-driven investing in the asset management industry. Unlike prior and contemporaneous studies that rely on a single proxy, often within a specific fund category or asset class, we use multiple data sources to examine the asset management industry and identify advisers and individual funds in which AI likely drives investment decisions. This approach uncovers AI-driven investing across a broad universe of funds and asset classes, distinguishing it from broader AI use cases such as operational workflow, and provides baseline descriptive evidence on the investment applications and fund-level performance of this technology in asset management.

Our paper also contributes to the hedge fund literature by exploring AI as an understudied source of performance. Prior research has attributed hedge fund performance to share liquidity restrictions (Aragon, 2007), managerial incentives and discretion (Agarwal, Daniel, and Naik, 2009; Gupta and Sachdeva, 2025), hedging choices (Titman and Tiu, 2011), strategy distinctiveness (Sun, Wang, and Zheng, 2012), and portfolio disclosure (Shi, 2017). The literature also documents associations between performance and both fund-level and manager-level characteristics.[3] We add to this literature by showing that funds with disclosed AI-driven strategies outperformed in the early part of the sample and relative to sibling funds, while their outperformance declined over time.

The decline in AI fund performance we document is consistent with theoretical discussions on the Adaptive Markets Hypothesis (Lo, 2004) and the competitive exploitation of machine

[3]For example, see Aggarwal and Jorion (2010), Li, Zhang, and Zhao (2011), Lu, Ray, and Teo (2016), Brown, Lu, Ray, and Teo (2018), Franzoni and Giannetti (2019), Zheng and Yan (2021), Lu and Teo (2022), and Lu, Naik, and Teo (2024).

learning (Allen, Kacperczyk, and Kumar, 2025, 2026). Financial markets are inherently non-stationary, and successful AI strategies erode the opportunities they exploit through reflexive dynamics. This alpha decay also aligns with earlier research on diminishing returns in active asset management. The prior literature has focused on decreasing returns to scale at both the fund level (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Fung, Hsieh, Naik, and Ramadorai, 2008; Zhu, 2018) and the industry level (Pástor and Stambaugh, 2012; Pástor, Stambaugh, and Taylor, 2015). Our findings suggest that the growth of AI funds and the broader quantitative investment ecosystem tend to make persistent outperformance increasingly difficult to sustain.

Our findings add to the growing literature on AI's impact across the finance industry. Recent studies examine the effects of AI adoption in public firm disclosures (Cao, Jiang, Yang, and Zhang, 2023; Cao, Jiang, Wang, and Yang, 2024), security trading strategies (Dou, Goldstein, and Ji, 2025; Colliard, Foucault, and Lovo, 2026), startup innovation (Bonelli, 2025), lending markets (Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022; Piao, Wang, and Weng, 2024; Choi, Huang, Yang, and Zhang, 2025; Gambacorta, Sabatini, and Schiaffi, 2025), and insurance sales (Liu, 2025). We contribute to this literature by examining AI-driven investing in the asset management industry and its performance in hedge funds.

More broadly, our paper relates to recent research on AI's impact on firm performance. Using US public firms, Babina, Fedyk, He, and Hodson (2024a) show that AI-investing firms experience increased growth in sales, employment, and market valuations, especially for larger firms. Relatedly, Czarnitzki, Fernández, and Rammer (2023) find a positive relationship between German firms' AI adoption and productivity, and Adams, Fang, Liu, and Wang (2026) find that AI-driven pricing strategies adopted by larger firms accelerate their growth. Eisfeldt, Schubert, Taska, and Zhang (2026) document that firms with greater exposure to generative AI experienced significantly higher firm value growth than less-exposed firms following the release of ChatGPT. Complementing this firm-level evidence, we show that

AI adoption in asset management concentrates in a subset of fund products and strategies rather than scaling uniformly with adviser size.

2. Data

We describe in this section the construction of our data sample and provide summary statistics of the main variables.

2.1. Investment adviser firm-level variables

This subsection describes firm-level data on investment advisers.

2.1.1. Form ADV

Investment advisers are required to register with the U.S. Securities and Exchange Commission (SEC) by filing Form ADV. These annual filings provide comprehensive information about advisers' business structures. We obtain all Form ADV filings submitted between 2012 and 2024 from the SEC website and extract data from several "Items" and the corresponding "Schedules" in Part 1A of the form. Specifically, Item 1 reports an adviser's identifying information. Item 5 reports an adviser's Regulatory Assets Under Management (RAUM), including decomposed values by client type.[4] Item 7B indicates whether an adviser manages private funds. Schedule D of Item 7B further provides detailed fund-level information for private funds, including fund types and gross asset values (GAV).[5]

We use the data starting in 2012, as significant updates to Form ADV for implementing the *Dodd-Frank Act* became effective in March 2012. The updates include raising the threshold for registration to $100 million in Regulatory Assets Under Management (RAUM), requiring

[4] In Form ADV, a client is either a legal entity (e.g., investment fund) or a person (e.g., a retail advisee).

[5] AUM is measured net of liabilities and does not include uncalled commitments, whereas GAV is reported fund gross assets, which include commitments and do not deduct liabilities.

a decomposition of RAUM by client types, and adding fund-level disclosures for private funds' types, gross asset values, ownership structures, and service providers.[6] In October 2017, the SEC amended Form ADV, leading to changes in the format of several items. For example, prior to 2017Q3, the amount of the adviser's RAUM attributable to a type of client was reported as a categorical range in Item 5D, including "None", "Up to 25%", "Up to 50%", "Up to 75%", and ">75%". After 2017Q3, Item 5D was revised to report the exact amount of RAUM. To ensure consistency in measuring business dimensions across years, we convert categorical ranges into numerical values by taking the midpoint of the range (e.g., "Up to 50%" becomes 37.5%). Moreover, if the reported RAUM attributable to a type of client is missing, we impute the value as zero.

Form ADV Part 2A (the "Brochure") requires registered advisers to describe their methods of analysis and investment strategies in Item 8. We obtain 116,276 brochures filed between 2012 and 2024, representing 62,253 adviser-years, to investigate AI-driven strategies among U.S. investment advisers. We first identify filings that mention AI-related and quant-related keywords and then use OpenAI's GPT-5 model to classify each AI-related filing into one of five categories:[7] (1) AI-Autonomous, where AI/ML is the primary engine for investment decisions; (2) AI-Augmented, where AI/ML significantly informs investment decisions made by humans; (3) AI Support, where AI is used for research support functions that do not directly contribute to investment decisions, such as summarizing materials, cleaning data, and generating reports; (4) AI-Theme Assets, where the adviser invests in AI-related companies; and (5) AI Risk Disclosure, where AI is mentioned only in risk disclaimers. As mentioned earlier, we define both (1) and (2) as AI-driven investing. The classification prompt and

[6]Investment advisers with RAUM of at least $100 million are eligible for SEC registration and are required to register at $110 million or more. In practice, advisers typically register with the SEC once they become eligible, allowing them to avoid the complexities of state-level registration. Moreover, advisers with RAUM below the $100 million threshold may also file Form ADV, even if they are not registered with the SEC. To avoid selection biases, our sample includes Form ADV filings by advisers in years with at least $100 million RAUM.

[7]Each filing is assigned to exactly one category. When a filing is consistent with more than one category, the classifier follows a strict priority order from (1) to (5).

examples are provided in the Internet Appendix.

2.1.2. Job postings from Lightcast

Lightcast (previously known as Burning Glass) aggregates job postings from a variety of online sources, including both job boards and company websites. The dataset includes the full job description and extracted data items such as employer names, job titles, posting dates, sought-after skills, and educational prerequisites.[8] Our Lightcast sample covers U.S. job postings from 2010 to 2024. We focus on entries with available employer names and exclude internships.

Our primary measure of an investment adviser's AI adoption is AI labor intensity, defined as the fraction of AI-related job postings among its total job postings in a year. Because firms rarely disclose their AI-specific capital expenditures, the literature often measures firm-level AI adoption using labor market data.[9] Following the methodology in Babina, Fedyk, He, and Hodson (2024a), we classify AI-related job postings based on the required labor skills. Appendix IA.1 details the steps for constructing this measure. To reduce the influence of outliers, we require each adviser-year observation to include at least five job postings.

2.1.3. Adviser-year panel

We construct an adviser-year panel by linking Form ADV filings with Lightcast job postings as follows. First, we retain all filings in which the adviser's total RAUM is non-zero and non-missing. For each adviser, uniquely identified by its SEC file number, we keep only the last filing submitted within each calendar year.

Second, we process the private funds data and compute each adviser's total number of

[8]Hershbein and Kahn (2018) find that while Lightcast data focus more on specific occupations and industries, their distribution patterns are relatively consistent over time and align with vacancy trends reported by other major data sources (e.g., Job Openings and Labor Turnover Survey, the Current Population Survey, and Occupational Employment Statistics).

[9]See, for example, Acemoglu, Autor, Hazell, and Restrepo (2022), Babina, Fedyk, He, and Hodson (2024a), Babina, Fedyk, He, and Hodson (2024b), and Eisfeldt, Schubert, Taska, and Zhang (2026).

private funds and their aggregate GAV. We also calculate private fund GAVs separately by fund type: Hedge Funds, Private Equity Funds, Real Estate Funds, Securitized Asset Funds, Venture Capital Funds, and other private funds.[10] We then merge private fund variables with the adviser-year panel using the unique filing identifier.

Third, we construct a linktable between investment advisers in Form ADV and employers in Lightcast, using Morningstar's PitchBook platform. PitchBook applies a proprietary entity-matching algorithm that incorporates firm name variations (e.g., legal names, trade names, former names), headquarters locations, and website URLs. The algorithm also accounts for parent-subsidiary relationships. Figure IA.3 in the Appendix summarizes the annual distribution of linked investment advisers. In terms of total assets under management, almost all Form ADV filers are matched to PitchBook entities, and approximately 70% of those are further linked to job postings in Lightcast.

2.2. Fund-level variables

We use the Hedge Fund Research (HFR) database for information on fund size, returns, contract terms, and investment strategies. We choose HFR because it offers superior coverage of fund data in recent years, when AI-related activities became especially relevant.[11] More importantly, HFR consistently provides detailed fund-level strategy descriptions, typically with at least 100 words, which we use to identify AI-driven investing through textual analysis.

Using commercial hedge fund databases could introduce two potential biases. First, the standard HFR database includes both live and dead funds, but it reports fund investment

[10] Our data cleaning involves three steps. First, we reclassify funds originally labeled as "Other Private Funds" into one of the five core types whenever the fund type description provides a clear mapping. Second, if a private fund has a missing type or is reported as a "Liquidity Fund," we recode it as "Other Private Fund." Third, we ensure consistency between the Item 7B indicator for advising private funds and the presence of private fund data in Schedule D.

[11] Agarwal, Daniel, and Naik (2004) compare the number of hedge funds covered in three major databases, HFR, ZCM/MAR, and Lipper TASS, during the period 1994–2000, and find that HFR offers the most comprehensive coverage. We also compare HFR and Lipper TASS over the period 2010–2024 and find that HFR offers substantially better fund coverage.

strategies and contractual terms only as of the last available date of each fund. Using this information retrospectively over the life of a fund could introduce a look-ahead bias. For example, hedge fund advisers may selectively adopt (or disclose the use of) AI strategies in funds with better past performance. Second, historical data may be selectively added into the database when a fund was included for the first time, generating a backfilling bias.[12] To address these concerns, we acquire year-by-year archived snapshots of the HFR database from 2005 to 2024, where each snapshot contains only information available as of that year. For each fund-year, we assign the contractual terms and strategy description from the most recent available snapshot as of the prior year-end, which eliminates the look-ahead bias. We then keep data of a fund starting from the first year in which it appears in a snapshot to avoid the backfilling bias.

As noted in the literature, hedge fund databases may list multiple share classes of the same fund as separate entries (e.g., Aggarwal and Jorion, 2010). To address this, we consolidate share classes to the unique portfolio level by computing pairwise return correlations among all funds within the same management firm and grouping those with correlations of at least 0.99 using a connected-components algorithm. For portfolios with multiple share classes, we aggregate returns as the equal-weighted mean and total net assets as the sum across share classes, except when all share classes report identical values, in which case we take the maximum to avoid double-counting fund-level totals. AI and quantitative strategy indicators are set to the maximum within each portfolio-year to ensure consistent classification.

We use OpenAI's GPT-5 large language model to analyze fund investment strategy descriptions in each yearly snapshot of the HFR database and evaluate whether the fund employs AI technologies for investment decisions. To ensure the accuracy of this identification and minimize false positives, we design a stringent prompt and refine it through iterative manual inspection and fine-tuning. This conservative approach prioritizes high precision over

[12]See, for example, Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), and Malkiel and Saha (2005).

broad coverage, which might understate the prevalence of AI-driven investing but reduces false positives in the performance tests. In this process, we also identify funds that use quantitative strategies. The complete AI prompt and classification examples are provided in the Internet Appendix.

We estimate monthly fund alpha using two alternative benchmark models that are standard in the literature.[13] The first is the seven hedge fund factors from Fung and Hsieh (2004), which include the following factors: Equity Market, Size Spread, Bond Market, Credit Spread, and Trend-Following Factors for Bonds, Currencies, and Commodities.[14] The second benchmark is developed by AQR, including global Equity Indices, Fixed Income, and Commodity markets, and Value, Momentum, Carry, and Defensive factors, which are long-short style premia across all asset classes (Ilmanen, Israel, Lee, Moskowitz, and Thapar, 2021). For each month t, we estimate a fund's factor loadings by regressing its excess returns on factor returns over a 24-month window from $t-24$ to $t-1$, requiring at least 12 observations. We then compute the fund's alpha in month t as its excess return in t minus the product of these estimated loadings and the factor returns realized in month t.

To be consistent with our analysis of investment advisers, we restrict our sample to USD-denominated US-domiciled hedge funds. We use HFR's classification of hedge fund strategy categories, including Equity Hedge, Event Driven, Macro, Relative Value, Fund of Funds, Risk Parity, and Crypto/Blockchain.[15] Our fund-month panel sample for regressions requires funds to have non-missing size, alpha, and contractual information, and at least $5 million in AUM. These filters reduce the number of unique hedge funds from 7,896 to 5,894, leaving us with 324,952 fund-month observations. To mitigate the impact of outliers, we winsorize continuous variables at the 1st and 99th percentiles.

[13]Throughout this paper, we refer to alpha as the part of fund returns unexplained by benchmark models and use it for the purpose of performance evaluation, which does not imply mispricing or anomalies.

[14]Factor definitions and data are available at: https://people.duke.edu/~dah7/HFRFData.htm

[15]A complete list of HFR strategy categories and definitions is available at: https://www.hfr.com/hfr-indices/hfr-hedge-fund-strategy-classifications/.

In addition to hedge funds, we also create a dataset for mutual funds. We collect mutual fund investment strategy descriptions from Form 497K filings available on SEC's EDGAR database from 2009 to 2024.[16] Since 2010, the use of summary prospectuses has become widespread. Funds using summary prospectuses are required to file Form 497K at least annually and to provide updates when material changes occur. The summary prospectus follows a standardized format and item order. In this study, we focus on the section titled "Principal Investment Strategies of the Fund", which includes any investment techniques that are material to the fund's investment strategy. We apply the same AI prompt used for hedge fund strategy descriptions to process the investment strategy text of mutual funds.

2.3. Cross-Validation of AI measures

Our measures capture disclosed AI adoption. Because advisers' internal AI use is not directly observable, there is no gold-standard dataset for validating AI classifications. Moreover, both regulatory ADV filings and HFR strategy descriptions vary in their specificity, so our measures may not fully capture the true universe of AI-driven investing. We therefore assess the validity of our classifications by comparing them across independent data sources: adviser regulatory disclosures, fund strategy descriptions, AI-related job postings, and employee LinkedIn profiles. Although these sources are all based on disclosed or publicly observable information, they are collected from different settings and for different purposes. The consistent empirical relationships across these sources, as reported in Internet Appendix Section IA.2, suggest that our measures capture economically meaningful variation in AI adoption.

[16] Form 497K was introduced following SEC's adoption of the Summary Prospectus Rule (Rule 498) in 2009, which aimed to improve disclosure clarity in response to concerns that statutory prospectuses were excessively lengthy and difficult to navigate.

2.4. Summary statistics

Table 1 reports summary statistics for the adviser-year sample between 2012 and 2024. The average adviser has 1.17% of AI-related job postings. By construction, each adviser in the sample manages at least $100 million in AUM. The median adviser manages $5.6 billion in AUM and approximately 290 accounts.

Other variables measure the advisers' AUM composition. First, AUM% Discretionary is the proportion of AUM managed on a discretionary basis, where the adviser makes investment decisions without obtaining client approval for each trade. Advisers mostly operate under discretionary mandates, with a median discretionary AUM share close to 100%. Second, most advisers serve multiple types of clients. Roughly half of the advisers manage private funds, which are exempt from registration under the Investment Company Act of 1940, with an average of 28% of AUM in these funds. Mutual funds (including exchange-traded funds) refer to investment companies governed by the Investment Company Act of 1940. AUM% HighNetWorth is the proportion of AUM managed for high-net-worth individuals.[17] AUM% Individual is the proportion of AUM from retail investors who fall below the high-net-worth threshold. Third, advisers of private funds on average manage 13 private funds, with hedge funds having the largest share of gross asset values.

Table 2 presents summary statistics for our monthly hedge fund sample between 2006 and 2024. On average, only 1% of fund-month observations are classified as AI funds, which is comparable to the share of AI-related job postings in Table 1. By comparison, 23% of fund-months are classified as quant funds. The average fund is approximately $472.1 million in size and 10 years old, with a monthly return of 42 basis points and a monthly alpha of less than 10 basis points.

The average incentive fee among hedge funds in our sample is 15.7%, closely matching

[17] High-net-worth individuals are typically defined as clients with at least $1 million in liquid investable assets (excluding their primary residence).

the 16.3% reported in Agarwal, Daniel, and Naik (2009). High-water mark provisions are present in 86% of fund-month observations, consistent with the 80% prevalence in their sample. However, hurdle rate provisions appear less frequently in our sample. Management fee rates are generally between 1% and 2%. The average lock-up and restriction periods are 5.3 months and 4.5 months, respectively.

3. The Prevalence of AI-Driven Investing

This section documents the prevalence of AI-driven investing using three complementary approaches: AI disclosures in regulatory filings, AI-related job postings by investment advisers, and AI classifications of individual fund strategy descriptions.

3.1. AI-driven investing disclosed in Form ADV Part 2A

We begin with the universe of SEC-registered investment advisers' regulatory disclosures. Panel A of Figure 1 presents the number of advisers mentioning AI in their Part 2A filings by category. The total number of these advisers has grown from fewer than 10 in 2012 to nearly 300 in 2024. However, the sharp increase in 2023–2024 is largely driven by AI Risk Disclosures, AI-Theme Assets, and AI Support—categories that do not reflect a deep use of AI in investment decisions. In contrast, advisers using AI-Autonomous and AI-Augmented strategies have grown steadily but modestly. These patterns suggest that AI-driven investing has existed since the early 2010s and has grown at a slower rate than the recent surge in AI-related disclosures.

Panel B shows investment advisers using AI-driven strategies as subsets of all advisers using quantitative strategies in each year. Among the approximately 1,550 advisers disclosing quantitative strategies in 2024, around 100 explicitly mention the use of AI-Autonomous or AI-Augmented strategies. This suggests that AI-driven investing, while growing, remains a small and specialized niche within the quantitative investment space.

3.2. The growth of investment advisers' AI job postings

Panel A of Figure 2 presents time trends in AI-related job postings in SEC-registered investment advisers, Compustat financial firms, and Compustat non-financial firms. While the average share of AI-related job postings among all job postings remains below 4% across all three groups, it grows steadily before 2016 and rises sharply around 2017, with investment advisers persistently exhibiting a higher AI labor intensity following this take-off. In 2023, a notable decline in AI labor intensity is observed among Compustat non-financial firms, whereas investment advisers and Compustat financial firms are less affected. The annual averages for Compustat firms in our sample closely align with the patterns reported by Babina, Fedyk, He, and Hodson (2024a).

To shed light on the roles AI labor plays within investment advisers, we report in Panel B the average time trends of AI-related job postings across functional areas: investment, data management, IT, and client communication.[18] AI jobs for investment roles have consistently been the largest category through 2022. Since then, AI-related IT hiring has spiked, likely reflecting the adoption of generative AI.

3.3. Investment advisers' fund composition and AI job postings

We next examine the cross-sectional relationship between an investment adviser's AI labor intensity and the composition of the funds it manages. In Panel A of Table 3, column 1 shows that the natural logarithm of an investment adviser's total AUM is positively and significantly associated with the share of AI-related job postings in the following year. Column 2 shows that for a given level of AUM, the natural logarithm of the total number of client

[18] We classify AI-related job postings into four functional areas based on O*NET occupation codes: investment (e.g., financial risk specialists), data management (e.g., database administrators), IT (e.g., software developers), and client communication (e.g., marketing managers).

accounts is negatively associated with AI labor intensity, indicating that advisers managing larger accounts (e.g., investment funds rather than retail accounts) tend to invest more in AI. Figure IA.4 in the Internet Appendix visualizes these two correlations using a heatmap that double-sorts investment advisers by AUM and account count.

Columns 3 and 4 reveal a positive relationship between private funds and AI labor intensity. Column 3 shows that, on average, advisers managing private funds exhibit a 0.72-percentage-point higher AI labor intensity. This association is economically large, amounting to 61.5% of the sample mean and 14.8% of the sample standard deviation of AI labor intensity. Column 4 confirms this relationship using continuous measures of AUM composition. Controlling for the fraction of assets managed under discretionary mandates, a one-standard-deviation increase in the fraction of AUM in private funds (equal to 38.8 percentage points) is associated with a 0.54-percentage-point increase in AI labor intensity in the following year (i.e., 38.8×0.014). This corresponds to around 46.2% of the sample mean and 11.1% of the standard deviation. In contrast, the fractions of AUM in mutual funds (including ETFs), high net worth individuals, and other individual clients are all negatively associated with AI labor intensity.[19]

Given that involvement in private fund management is positively associated with future AI labor intensity, in Panel B, we further investigate this relationship by focusing on the subsample of advisers that manage private funds. In column 1, the coefficient on total GAV of private funds is positive and statistically significant. Column 2 shows that, conditional on private fund total GAV, the adviser's total AUM is no longer correlated with AI. This result is consistent with the notion that the association between adviser AUM and AI labor intensity in Panel A is mainly driven by private funds. In column 3, the number of private funds shows a significant negative association with AI labor intensity, suggesting that AI investments are more concentrated in advisers overseeing fewer, larger private funds.

Column 4 further examines the composition of private fund assets and shows that AI

[19]Figure IA.5 in the Internet Appendix visualizes these relationships with heatmaps.

labor intensity is positively associated with only one type of private funds: hedge funds. A one-standard-deviation increase in the fraction of GAV in hedge funds predicts a 0.83-percentage-point increase in AI labor intensity, equivalent to 71% of the sample mean and 17% of its standard deviation. In contrast, the fractions of GAV in other types of private funds are all negatively correlated.[20] Overall, Table 3 shows that among investment advisers, firm-level AI labor intensity is positively associated with larger total assets and a higher degree of asset concentration in their larger funds. Conditional on asset size, AI labor intensity is further positively related to advising a particular type of private funds: hedge funds.

In Appendix IA.1, we conduct robustness tests using alternative labor-based measures for an investment adviser's AI adoption, including an alternative classification of AI-related job postings in Abis and Veldkamp (2024) and a measure of data-related occupations based on LinkedIn profiles from Revelio Labs. Overall, we find a similar and robust relationship between fund composition and AI adoption at the adviser level.

3.4. The growth of AI hedge funds in the HFR database

Now we focus on AI-driven investing at the individual fund level. In our data, there are 7,896 unique hedge funds between 2006 and 2024, of which 89 (1.1%) are ever identified as AI funds. This small fraction reflects our strict criteria for identifying AI-driven investing based on fund strategy descriptions. Panel A of Figure 3 shows the time-series growth of AI hedge funds, in terms of both total AUM and the number of funds. Panel B scales these two measures by the total AUM and the number of all hedge funds in our sample, which addresses the influence of changes in the coverage of the hedge fund database.

Both the number and percentage of AI hedge funds have increased steadily since 2006. This increase accelerated around 2017, coinciding with the rise in AI labor intensity in Figure 2. The number of AI hedge funds reached its peak in 2023 accounting for approximately 2.7%

[20]These relationships are visualized in Figure IA.6 in the Internet Appendix.

of hedge funds. In terms of the AUM of AI hedge funds, the total amount and percentage grew substantially from 2021, reaching approximately USD 12 billion by 2024. These trends underscore the rapid expansion of AI-driven investing among hedge funds.

Internet Appendix Figure IA.7 divides the AI hedge funds into AI-Autonomous and AI-Augmented strategies, using a prompt similar to that in Section 3.1. It shows that AI-Autonomous funds account for roughly two-thirds of AI fund counts and over 90% of AI AUM in 2024. Internet Appendix Figure IA.8 further classifies the AI techniques used by these funds, summarizing their learning paradigms and model approaches.

Finally, when we apply the same GPT prompt to mutual fund investment strategy descriptions, we identify very few AI mutual funds. This finding is consistent with Table 3, Panel A, where the variable AUM% Mutual Fund exhibits a weak, negative correlation with future AI labor intensity. We report AI mutual funds' growth in Figure IA.9 in the Internet Appendix. At its peak in 2024, AI mutual funds and ETFs represented a minimal share of the public fund sector. Given these findings, the rest of the paper focuses on hedge funds.

4. The Characteristics of AI Hedge Funds

In this section, we examine AI-driven investing across hedge fund strategy categories and compare fund characteristics and factor exposures between AI funds and non-AI funds.

4.1. Investment strategies of AI hedge funds

The suitability and effectiveness of AI-driven investing likely differ across investment strategies, depending on the underlying assets, information environment, and trading frequency. Figure 4 shows the distribution of AI and non-AI hedge funds across main strategy categories, using all sample funds as of the last available date of each fund. Each of the four panels compares the share of AI funds (blue bars) and non-AI funds (white bars), where the share is calculated as the number or AUM of funds in a given category divided by the total number or AUM of AI (or non-AI) funds.

Panels A and B display the main strategy categories on the horizontal axes. In Panel A, the number of AI hedge funds is disproportionately high in Macro strategies, while being notably underrepresented in Event Driven, Relative Value, and Fund of Funds strategies. Equity Hedge also accounts for a large share of AI funds, but its relative weight is similar to that observed among non-AI hedge funds. When measured by AUM in Panel B, this pattern becomes even more pronounced: among funds with non-missing AUM data, over 80% of observed AI hedge fund assets are allocated to Macro strategies. Panels C and D display the subcategories within Macro on the horizontal axes. Among AI hedge funds in macro strategies, roughly 70% by number of funds and over 90% by AUM fall into a narrowly-defined sub-strategy called Systematic Diversified Macro. While this sub-strategy also dominates among non-AI macro hedge funds, its dominance is more pronounced among AI hedge funds.

The popularity of AI-driven investing in macro strategies provides a new perspective that complements the existing literature's focus on equities. Macro assets, such as commodities, fixed income, currencies, and equity indices, have a smaller cross section than equity markets, creating a "small data" challenge for training models (Kelly and Xiu, 2023). However, these assets are traded in highly liquid markets with prices tightly linked to global economic fundamentals, making them well-suited to AI-driven strategies that implement flexible short-term trading. For example, BlackRock (2025) provides a practitioner perspective on why macro strategies are particularly amenable to machine learning despite the data limitation.[21]

4.2. Contract terms and risk exposures of AI hedge funds

We compare AI funds and non-AI funds through a univariate analysis. We first compute fund-level averages of characteristics and then compute the averages across funds within AI

[21] Consistent with this, in our sample, BlackRock's Absolute Macro Fund, classified as AI-driven since 2021, operates within the Systematic Diversified Macro category.

and non-AI groups. In Table 4, the columns "AI" and "Non-AI" report the between-fund average values for AI funds and non-AI funds, respectively. The "Difference" column shows the average in the AI group minus the average in the non-AI group.

Panel A focuses on fund characteristics and highlights two distinguishing traits of AI hedge funds. First, all AI funds use quantitative strategies, whereas only 25.7% of non-AI funds are quant funds. Second, AI funds charge nearly 2.5 percentage points higher incentive fees and have a substantially lower likelihood of imposing a hurdle rate, meaning that investors pay performance fees more easily and at higher rates. At the same time, they impose around 60% shorter lockup and restriction periods, allowing investors to redeem capital more easily.

Panel B compares fund risk exposures using factor loadings. First, we consider the Fama–French stock market, size, and value factors. AI funds exhibit significantly lower loadings on all three factors, indicating a lower exposure to traditional risk premia in the US equity market. We next examine Fung–Hsieh factors. AI funds display a significantly lower exposure to the small-cap factor, corroborating that they tend not to pick illiquid individual stocks or trade on firm-specific information. They also display nearly zero exposure to the credit spread factor, which is significantly higher than that of non-AI funds, indicating an ability to hedge stress in credit markets. The third set of comparisons uses the AQR factors. Again, AI funds load significantly less on Equity Indices. They also exhibit a higher exposure to the Fixed Income factor, but the difference is statistically insignificant. In terms of all-asset-class style premia, AI funds have significantly negative loadings on Value, Carry, and Defensive factors but a higher, positive loading on the momentum factor, suggesting their distinctive exposures to global assets.

Taken together, the results in Table 4 show that AI funds exhibit substantially different exposures to asset classes and risk factors. This distinctiveness underscores the importance of adjusting their returns for the relevant risk premia when evaluating the performance of AI-driven investing.

5. The Performance of AI Hedge Funds

The performance of AI funds is central to understanding AI-driven strategies. In this section, we use our fund-month sample to examine whether AI funds generate superior benchmark-adjusted returns. In addition, we examine whether these funds attract additional flows to assess how investors respond to AI-driven investing in their capital allocation decisions.

5.1. Performance of AI funds relative to other hedge funds

We test the relative performance of AI funds by regressing benchmark-adjusted fund returns in the next month on current fund characteristics. Our variable of interest is an indicator variable for whether the fund is currently classified as an AI fund. We control for whether the fund employs a quantitative strategy to distinguish AI funds from other quant funds. We also control for fund contractual terms, size, and age. Moreover, our specifications include strategy-by-month fixed effects to compare AI funds with contemporaneous non-AI funds facing similar strategy-level opportunities.

Importantly, the AI indicator used to predict next-month performance is determined from archived HFR snapshots available as of the prior year-end. Thus, a fund's AI status is assigned before the return is realized. This design prevents the AI indicator from being assigned using performance realized after the classification date.

Table 5 reports our estimation results. In the first three columns, we measure performance using monthly alpha based on the Fung–Hsieh factors ("FH Alpha"). The point estimate in column 1 shows that between 2006 and 2024, the difference in monthly performance between AI and non-AI funds is around 8.4 basis points and is statistically indistinguishable from zero. In column 2, we include an interaction term AI×Year, where Year is the current calendar year minus 2006, the first year in our sample. Once this interaction term is included, the coefficient of the AI indicator variable becomes large and statistically significant. Our estimates indicate that, on average, AI funds' outperformance declines by 5.9 basis points per year.

In column 3, we replace the variables of interest with two interaction terms indicating whether the observation is an AI fund-month before and after December 2017, respectively.[22] Our estimates show that AI funds outperform non-AI funds by 49.6 basis points per month before 2017, and that this outperformance disappears after 2017. In columns 4 to 6, we use alpha based on the AQR factors as an alternative measure of fund performance ("AQR Alpha") and find qualitatively similar results with magnitudes that are slightly smaller. Our results in Table 5 suggest that, in earlier years, AI funds substantially outperform their non-AI counterparts. However, their outperformance diminishes in subsequent years as AI-driven investing grows among hedge funds.[23] In Internet Appendix Table IA.5, we re-estimate the performance regressions while dividing AI hedge funds into AI-Autonomous and AI-Augmented strategies and find that the earlier outperformance of AI funds is concentrated among AI-Autonomous funds.

A potential explanation for the diminished outperformance is that AI funds launched in earlier years may be inherently better than those launched in later years. If so, early adopter AI funds may continue to outperform non-AI funds even after 2017. To examine this possibility, we classify AI funds as either early or late AI adopters based on whether the first year the fund is identified as an AI fund is before or after 2017. We then estimate regressions of fund performance on interaction terms involving the AI indicator variable, the Early/Late Adopter dummies, and the Before/After 2017 dummies.

Table 6 reports our estimation results. Similar to the previous table, we find that early-adopter AI funds significantly outperform non-AI funds before 2017. However, after 2017, their performance disappears based on FH alpha and even reverses based on AQR alpha, while late adopters show no significant performance difference from non-AI funds. This result

[22]We use December 2017 as the cutoff because 2017 is the year when the growth of AI funds accelerated, as shown in Figure 3, coinciding with the rise in AI-related job postings documented in Figure 2.

[23]Internet Appendix Figure IA.10 plots the annual alpha of each individual AI fund and shows that the earlier outperformance and its subsequent decline also exist in absolute terms and are not driven by outliers.

suggests that the disappearance of AI funds' outperformance reflects a trend among all AI funds rather than a difference between early and late AI adopters.

The diminished outperformance of AI funds is consistent with two mechanisms. First, the Adaptive Markets Hypothesis of Lo (2004) suggests that profitable trading opportunities are transient, and AI/ML strategies alter the data-generating process that created these opportunities, causing returns to decay through competitive exploitation (Allen, Kacperczyk, and Kumar, 2025, 2026). Second, the competitive pressure from the broader quantitative investment ecosystem—including firms that use AI/ML methods without explicit disclosure—may erode the opportunities available to all AI-driven strategies, consistent with industry-level decreasing returns to scale in active management (e.g., Pástor and Stambaugh, 2012).

We also consider an alternative measure of performance in the spirit of Berk and van Binsbergen (2015), by computing the average monthly "net value added" (Ardia and Barras, 2026) over each fund's lifetime. We find that AI funds and non-AI funds generate similar value added, with a statistically insignificant difference at conventional levels. This result is consistent with competitive equilibrium: AI funds' higher net alpha is offset by their smaller average assets under management.

5.2. Performance of AI funds relative to sibling funds

AI funds are managed by a subset of hedge fund advisers. Hence, any difference in performance between AI and non-AI funds may also reflect heterogeneity across hedge fund advisers.[24] For example, advisers with better firm-level resources might self-select to launch AI funds. If that was the case, our fund-level analysis could have overstated the performance associated with AI-driven investing. Alternatively, after paying fixed costs for AI infrastructure, advisers could share AI-generated signals among all their funds, benefiting funds that do not explicitly follow AI-driven strategies. This within-adviser spillover would imply that our analysis has

[24] Internet Appendix IA.3 examines the role of adviser characteristics in the creation of AI hedge funds.

underestimated the outperformance of AI funds.

To distinguish the performance associated with AI-driven investing from these firm-level confounding forces, we compare fund performance within the same adviser, across its sibling funds. Specifically, we saturate the baseline specifications in Subsection 5.1 with adviser-by-month fixed effects. This specification absorbs any time-varying adviser-level influences on fund performance and restricts the sample to adviser–months with at least two funds. The remaining difference in performance, if any, cannot be attributed to unobserved adviser characteristics or the spillover effects of AI investment on non-AI sibling funds.

Table 7 presents our estimation results. Over the sample period between 2006 and 2024, AI funds outperform sibling funds by 34.9 basis points per month using the FH alpha and by 41.1 basis points using the AQR alpha. This within-adviser difference is economically and statistically significant, ruling out the possibility that our baseline results are driven by unobserved adviser-level heterogeneity. The estimates in columns 2–3 and 5–6 suggest that the declining outperformance occurs even within advisers.

5.3. Comovement of AI fund performance

AI funds' declining outperformance potentially reflects strategy crowding: if AI funds trade on correlated signals of other funds, the collective impact of these funds could eliminate the opportunities they exploit. To examine this possibility, we examine the comovement of benchmark-adjusted returns of AI funds and their peer funds.

Table 8 reports our comovement tests. In Panel A, we compare the comovement between AI funds and between non-AI funds, using average pairwise correlations of monthly alphas for fund pairs within the same HFR strategy category.[25] Contrary to the crowding hypothesis, AI fund pairs exhibit *lower* average pairwise correlations than non-AI pairs. Using the FH

[25]For AI pairs, correlations are computed using only months in which both funds are classified as AI; for non-AI pairs, only months in which both are non-AI. Each pair requires at least 12 overlapping months.

alpha, the average correlation among AI pairs is 0.021, compared with 0.124 among non-AI pairs, a difference of -0.103 that is statistically significant. The difference is smaller but remains significant using the AQR alpha. Excluding fund pairs managed by the same adviser strengthens these results.

Panel B focuses on the comovement between AI funds and strategy peers by estimating panel regressions following Hunter, Kandel, Kandel, and Wermers (2014). We regress monthly fund alpha on the average alpha of all funds in the same strategy-month (excluding the fund itself) and interact this peer performance with the AI indicator. The coefficient on the interaction term AI $\times$ Peer Performance is negative and significant across all specifications, indicating that AI funds comove less with the common performance of their strategy peers than non-AI funds do.

Together, these results suggest that AI funds implement sufficiently diverse approaches. Specifically, their returns are less correlated with both other AI funds and with their strategy peers. This finding sheds light on widespread concerns that AI adoption amplifies strategy homogeneity and herding behavior (e.g., OECD, 2021; U.S. Senate Committee on Homeland Security and Governmental Affairs, 2024) and speaks against a simple homogeneity narrative. The low comovement we document is also consistent with the ecological specialization identified by Allen, Kacperczyk, and Kumar (2026), in which different ML model families occupy distinct niches within the market ecology.

5.4. Money flows to AI hedge funds

An important driving force behind the rapid growth of AI funds is investors' demand for AI-driven strategies, which is related to their belief in AI's alpha-generating ability. As highlighted in Pástor and Stambaugh (2012), investors' slow learning about both this ability and returns to scale drives the size of the active management industry. To examine investor beliefs about AI's alpha-generating potential, we apply a revealed preference approach and analyze money flows into hedge funds.

We test whether mentioning AI technologies in strategy descriptions attracts inflows beyond what can be explained by realized performance and other fund characteristics. Specifically, we regress monthly net fund flow on the AI indicator variable while controlling for fund performance, measured with a lagged 12-month rolling-window average FH alpha. We also control for other fund characteristics and strategy-by-month fixed effects.

Table 9 reports our estimation results. Across all specifications, the AI coefficient is small and statistically insignificant. This result implies that investors do not systematically direct more capital to AI funds. In contrast, past performance strongly predicts flows: column 2 shows that a one percentage point increase in lagged 12-month alpha is associated with a 34.5 basis points higher monthly inflow. Column 3 controls for the indicator for quant strategies, which does not attract extra flows either. In column 4, we further include fund contractual terms and find that lockup and restriction periods are associated with higher inflows, whereas management fees are associated with lower inflows. Overall, we find no evidence that investors hold strong prior beliefs on AI's ability to generate superior performance or chase disclosed AI strategies.

5.5. Survival of AI hedge funds

Although our sample includes both live and dead funds, the requirement of at least 12 months of returns for alpha estimation could introduce an implicit survivorship bias (Baquero, Ter Horst, and Verbeek, 2005). To assess whether our findings are influenced by this potential bias, we compare the dropout rates of AI and non-AI hedge funds over different time horizons.

Table 10 presents a summary of dropout rates. A fund may drop out of the database either through liquidation or by ceasing to report. Panel A shows the total dropout rates, which reflect both sources of attrition. Across 1-month, 3-month, 6-month, and 1-year horizons, AI funds exhibit moderately higher average dropout rates than non-AI funds. Panel B shows that fund liquidation primarily drives the differences in the total dropout rates, potentially reflecting more intensive experimentation with AI strategies by fund advisers. However, these differences in both panels are statistically indistinguishable from zero. Panel C focuses on dropout rates due to ceased reporting and shows that AI and non-AI funds have very similar rates of ceasing to report to the database. Overall, these comparisons show that survivorship bias is unlikely to materially affect our findings.

6. Conclusion

This paper examines AI-driven investing in the asset management industry. Using investment adviser regulatory disclosures, labor market data, and fund strategy descriptions, we document a highly uneven pattern of AI adoption. AI-driven investing is concentrated among hedge funds and over-represented in those employing systematic diversified macro strategies. After adjusting for substantial differences in risk exposures, we find that AI funds significantly outperform non-AI funds in the early years, but this outperformance declines over time. Meanwhile, AI funds exhibit lower return comovement than non-AI peers, suggesting diverse rather than crowded investment approaches. These patterns are consistent with the Adaptive Markets Hypothesis, in which profitable trading niches are transient and eroded through competitive exploitation.

Several limitations of our analysis deserve discussion. First, our text-based AI classifications capture *disclosed* AI adoption. Some advisers and funds may not disclose their strategies that leverage AI/ML technology. As a result, the prevalence we document may not fully capture all AI-driven investing in the industry, which could also attenuate our estimated AI fund performance. Second, our tests based on labor data use a matched sample of advisers, which has limited coverage for smaller, specialized firms. Finally, our fund-level analysis relies on the HFR database, which covers a modest share of hedge fund assets reported in SEC Form ADV filings (Internet Appendix Figure IA.11). The number of AI-driven hedge funds we identify is relatively small, and AI technologies have evolved rapidly; therefore, extrapolating our estimates to future periods warrants caution. Despite these limitations, the consistent patterns across three independent data sources—fund strategy descriptions, adviser regulatory filings, and labor market data—provide new evidence on the growth of AI-driven investing. Moreover, the cross-sectional differences between AI and non-AI funds in strategy composition, contract terms, factor exposures, and performance could be informative even if we under-identify AI funds, as our conservative classification ensures high precision at the cost of false negatives.

Our findings have several implications. First, AI-driven investing per se does not necessarily predict better fund performance, and investors do not appear to chase disclosed AI strategies in allocating capital to funds. Second, the prevalence of AI-driven investing in macro asset classes opens new questions about how AI may affect efficiency and stability in commodity, currency, and fixed income markets, extending the literature beyond its traditional focus on equities. Third, for asset managers, the value of AI may lie not only in alpha generation but also in operational efficiency and cost reductions. Finally, the declining outperformance of AI funds suggests that the competitive dynamics of AI adoption in financial markets may differ from popular expectations of persistent advantages in non-financial applications.

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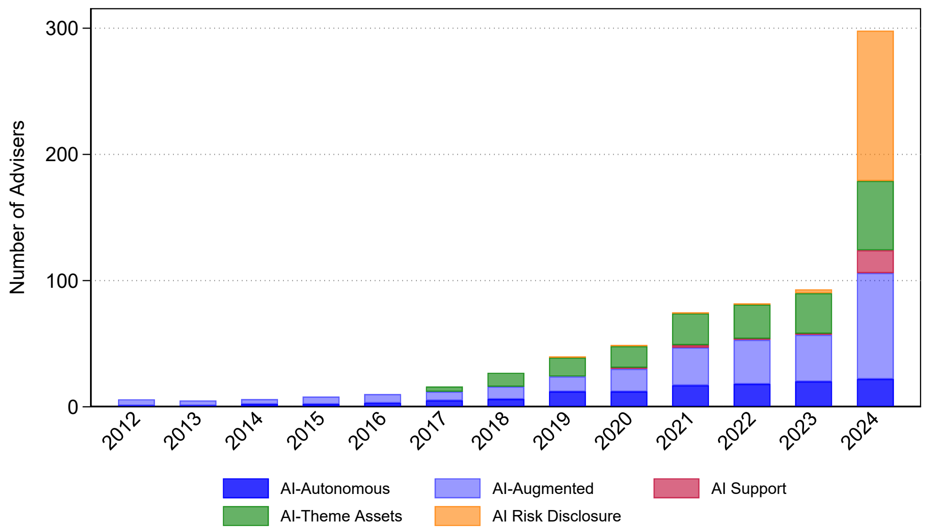
(a) AI Disclosures by Category



(b) AI and Quantitative Strategies

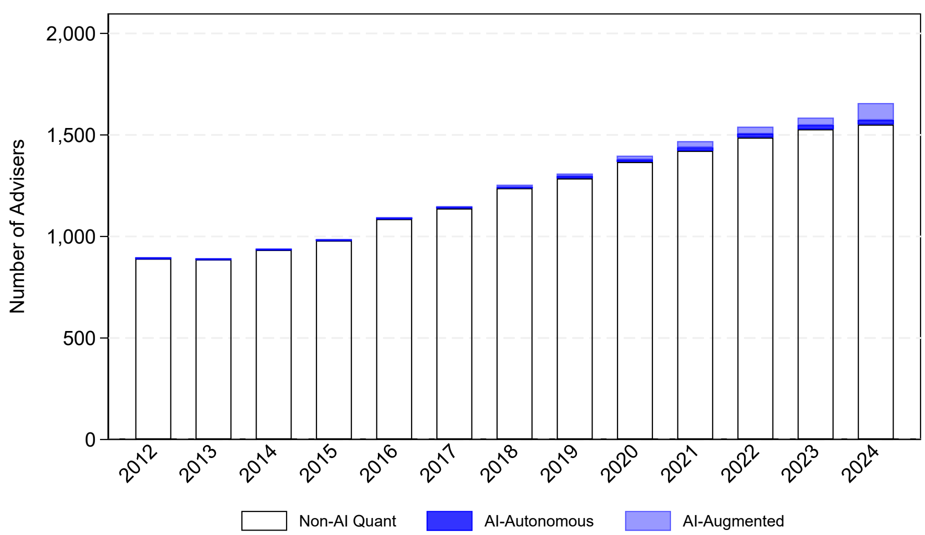
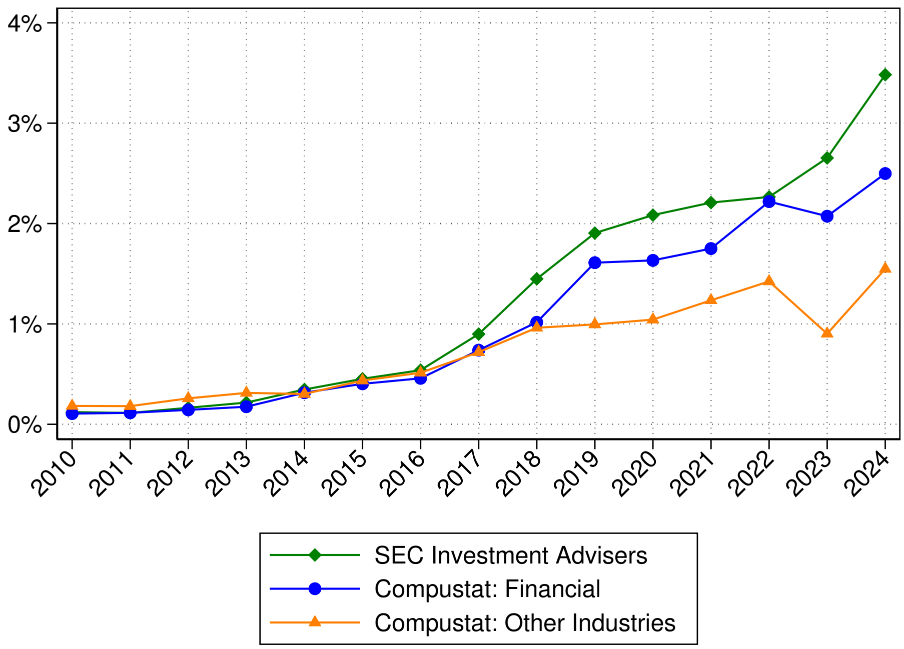


Figure 1: **AI and Quantitative Disclosures in Form ADV Part 2A.**
This figure summarizes AI and quantitative strategy disclosures by SEC-registered investment advisers in Form ADV Part 2A (Item 8). Panel A shows the number of advisers by AI disclosure category. Categories include AI-Autonomous (AI/ML is the primary investment decision maker), AI-Augmented (AI/ML meaningfully informs but does not directly drive investment decisions), AI Support (AI used for research support or operational tasks that do not directly contribute to investment decisions, such as data extraction, dataset cleaning, report generation, and compliance monitoring), AI-Theme Assets (strategies investing in AI-related companies), and AI Risk Disclosure (AI mentioned only in risk disclosures). Panel B shows advisers using AI-Autonomous and AI-Augmented strategies as subsets of the population of advisers using quantitative strategies.

(a) AI Job Postings by Investment Advisers and Compustat Firms



(b) Investment Advisers' AI Jobs for Specific Roles

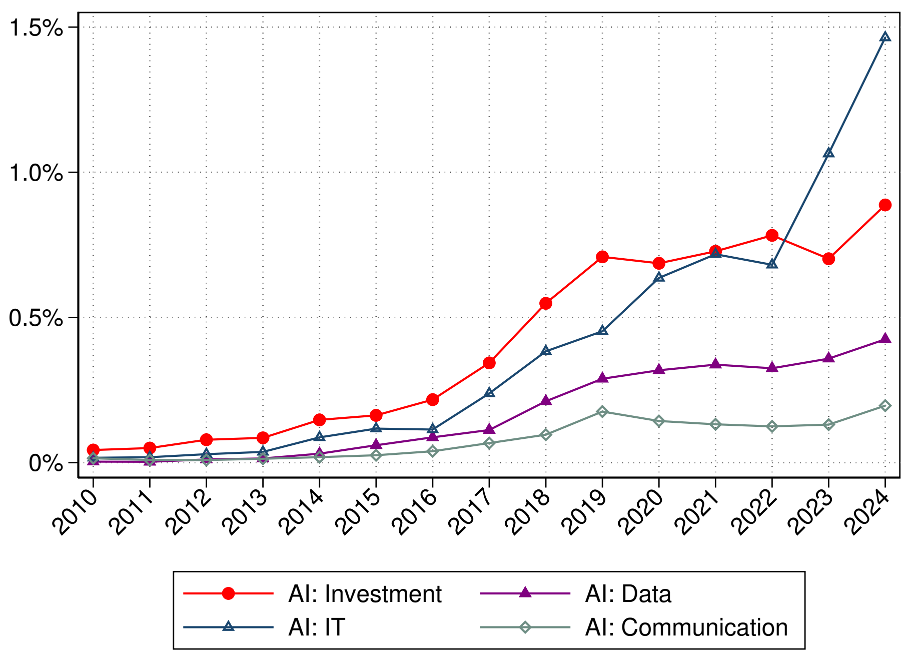
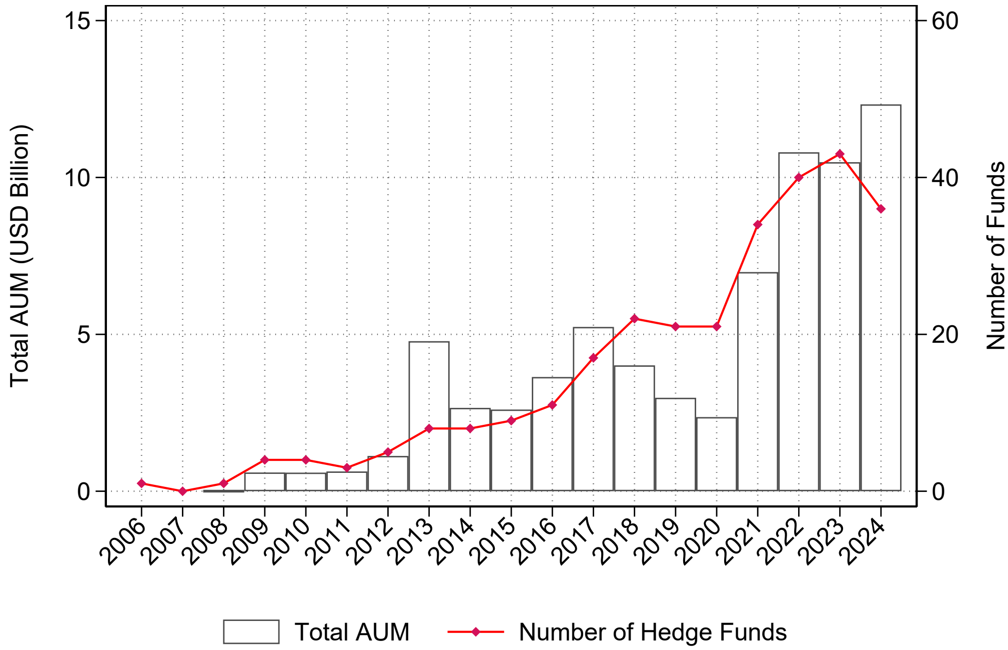


Figure 2: **AI Job Postings by Registered Investment Advisers.**
This figure summarizes AI-related job postings. Panel A shows the annual percentages of AI jobs among total job postings by each of three groups of firms: SEC registered investment advisers, financial industry firms in Compustat, and non-financial firms in Compustat. Panel B shows annual percentages of AI jobs for specific functional areas among total job postings by investment advisers. Functional areas are classified based on O*NET occupation codes.

(a) Number and AUM of Hedge Funds



(b) Percentage of Hedge Funds

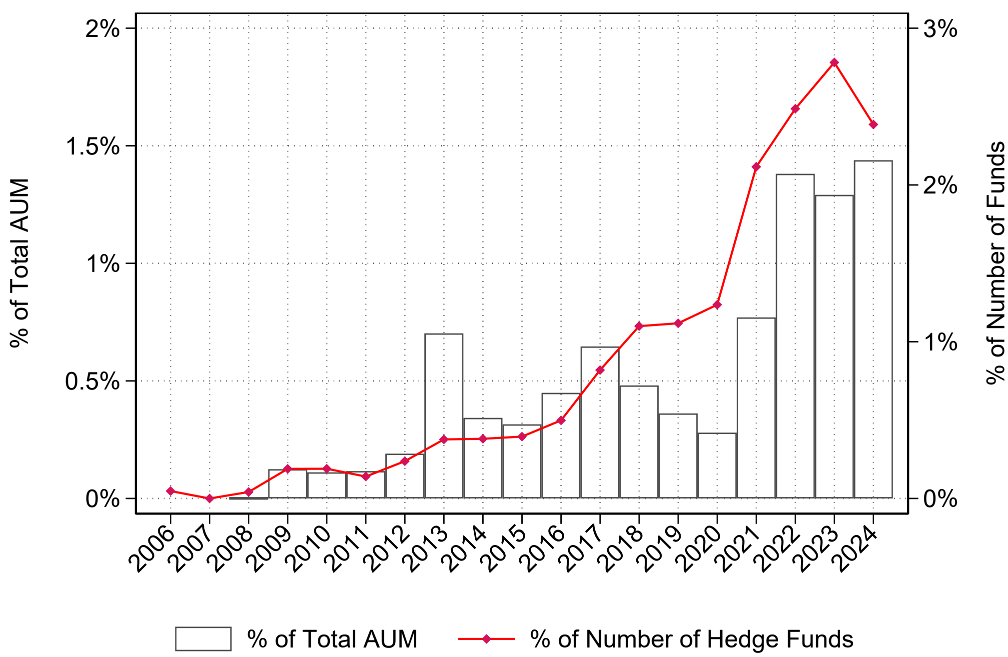


Figure 3: **The Growth of AI Hedge Funds.**
This figure presents the growth of AI hedge funds between 2006 and 2024. Panel A shows the number and total AUM of AI hedge funds by year. Panel B shows their number and total AUM as percentages of USD-denominated U.S. hedge funds in the HFR database.

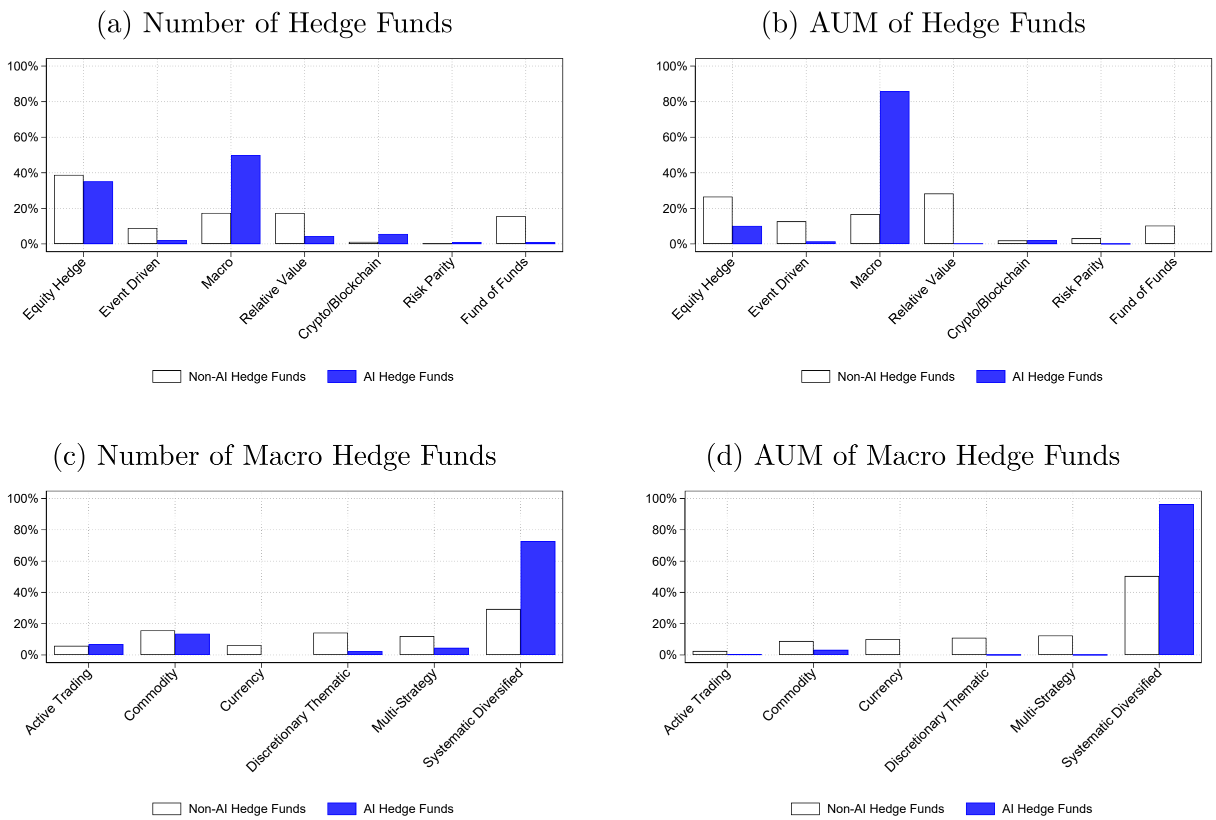


Figure 4: **Distribution of AI Hedge Funds By Strategy Categories.**
This figure compares the distribution of investment strategies between AI and non-AI hedge funds. The sample includes all USD-denominated U.S. funds ever included in HFR as of the last available date of each fund. Panels A and B show the distributions of the number and total AUM of hedge funds across main strategy categories, respectively. Panels C and D restrict to macro strategy hedge funds and show the distributions across sub-strategy categories in HFR.

Table 1: **Summary Statistics: SEC Registered Investment Advisers**

This table presents summary statistics for the sample of investment advisers. Every observation is an adviser-year between 2012 and 2024 with at least $100 million of current AUM and at least 5 job posts in the next year. AI% Job Posting is the percentage of AI-related jobs among the adviser's job postings. AUM is the adviser's total regulatory assets under management in billion USD. Account is the adviser's total number of managed accounts in thousands. Advise Private Fund is an indicator variable that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. GAV is the adviser's total private fund gross asset values in billion USD. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category.

	N	mean	sd	p10	p25	p50	p75	p90
AI% Job Posting	7,646	1.17	4.85	0.00	0.00	0.00	0.45	2.80
AUM	7,646	67.24	267.03	0.27	0.99	5.56	38.33	147.65
Account	7,646	29.27	265.36	0.00	0.02	0.29	4.04	28.60
Advise Private Fund	7,646	0.47	0.50	0.00	0.00	0.00	1.00	1.00
AUM% Discretionary	7,646	84.91	28.59	33.41	86.25	99.94	100.00	100.00
AUM% Private Fund	7,646	27.60	38.80	0.00	0.00	1.02	62.50	100.00
AUM% Mutual Fund	7,646	15.83	30.66	0.00	0.00	0.00	12.50	87.50
AUM% HighNetWorth	7,646	18.43	27.76	0.00	0.00	0.15	29.90	66.72
AUM% Individual	7,646	15.86	26.78	0.00	0.00	0.00	16.50	62.50
GAV	7,646	7.26	26.05	0.00	0.00	0.00	1.75	14.99
Number of Private Fund	7,646	13.60	41.23	0.00	0.00	0.00	7.00	33.00
GAV% Hedge Fund	3,599	34.95	42.59	0.00	0.00	3.76	87.46	100.00
GAV% Private Equity Fund	3,599	21.86	37.69	0.00	0.00	0.00	29.52	100.00
GAV% Real Estate Fund	3,599	12.51	31.09	0.00	0.00	0.00	0.00	90.69
GAV% Securitized Asset Fund	3,599	7.06	22.04	0.00	0.00	0.00	0.00	17.23
GAV% Venture Capital Fund	3,599	1.18	9.48	0.00	0.00	0.00	0.00	0.00

Table 2: **Summary Statistics: Hedge Funds**

This table presents summary statistics for the hedge fund sample. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. Return is the fund's net return in percentage points. Alpha is the fund's monthly out-of-sample alpha based on Fama-French three equity factors, Fung-Hsieh hedge fund factors, and AQR multi asset class factors. Flow is the net flow into the fund in percentage points. AI and Quant are indicator variables that equal one if the fund is classified as an AI fund and a quant fund, respectively. Incentive Fee and Management Fee are the incentive and management fees charged by the fund adviser. High Water Mark and Hurdle are indicator variables that equal one if the fund's compensation contract includes a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the fund's assets under management in USD million, and Age is the number of months since fund inception.

	N	mean	sd	p10	p25	p50	p75	p90
Return	324,952	0.42	3.62	-3.38	-0.94	0.50	1.85	4.07
Alpha: FF3	324,952	0.00	3.15	-3.31	-1.26	0.09	1.25	3.12
Alpha: FH	324,952	0.07	3.58	-3.61	-1.34	0.15	1.47	3.62
Alpha: AQR	324,952	0.08	3.57	-3.67	-1.36	0.12	1.48	3.71
Flow	324,952	-0.28	6.63	-5.03	-1.26	0.00	0.90	3.97
AI	324,952	0.01	0.08	0.00	0.00	0.00	0.00	0.00
Quant	324,952	0.23	0.42	0.00	0.00	0.00	0.00	1.00
Incentive Fee	324,952	15.68	7.51	0.00	10.00	20.00	20.00	20.00
High Water Mark	324,952	0.86	0.35	0.00	1.00	1.00	1.00	1.00
Hurdle Rate	324,952	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Lockup Period	324,952	5.30	7.37	0.00	0.00	0.00	12.00	12.00
Restriction Period	324,952	4.51	4.00	1.07	2.00	4.00	5.17	8.00
AUM	324,952	472.10	2474.72	12.00	27.57	79.00	274.48	881.40
Age	324,952	122.33	82.79	33.00	58.00	103.00	168.00	240.00
Management Fee	324,952	1.40	0.60	1.00	1.00	1.50	1.95	2.00

Table 3: **Investment Adviser's Fund Composition and AI Job Postings**

This table reports results from regressing the percentage of the investment adviser's AI-related jobs among its job postings in the next year on the current size and composition of its assets. Every observation represents an adviser-by-year between 2012 and 2023 with at least $100 million of current AUM and at least 5 job posts in the next year. Panel A uses the adviser's total assets under management (AUM), and the sample includes all adviser-years. AUM is the total regulatory assets under management. Account is the adviser's total number of managed accounts. Advise Private Fund is an indicator variable that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. Panel B uses the adviser's private fund gross asset values (GAVs), and the sample includes only adviser-years that manage private funds. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: AI% Job Postings, All Investment Advisers

	(1)	(2)	(3)	(4)
log(AUM)	0.253***	0.327***	0.260***	0.236***
	(0.040)	(0.047)	(0.045)	(0.046)
log(Account)		-0.192***	-0.144***	
		(0.035)	(0.031)	
Advise Private Fund			0.723***	
			(0.159)	
AUM% Discretionary				0.006***
				(0.002)
AUM% Private Fund				0.014***
				(0.004)
AUM% Mutual Fund				-0.005*
				(0.003)
AUM% HighNetWorth				-0.009***
				(0.002)
AUM% Individual				-0.001
				(0.002)
Year FEs	Y	Y	Y	Y
N	7,646	7,646	7,646	7,646
R^2	0.032	0.052	0.057	0.065

Table 3: **Investment Adviser's Fund Composition and AI Job Postings (Cont'd)**

Panel B: AI% Job Postings, Advisers of Private Funds

	(1)	(2)	(3)	(4)
log(GAV)	0.371***	0.365***	0.596***	0.493***
	(0.092)	(0.097)	(0.136)	(0.116)
log(AUM)		0.014		
		(0.064)		
log(Number of Private Fund)			-0.543***	-0.395**
			(0.176)	(0.165)
GAV% Hedge Fund				0.020***
				(0.007)
GAV% Private Equity Fund				-0.006
				(0.004)
GAV% Real Estate Fund				-0.004
				(0.006)
GAV% Securitized Asset Fund				-0.012***
				(0.004)
GAV% Venture Capital Fund				-0.008
				(0.005)
Year FEs	Y	Y	Y	Y
N	3,599	3,599	3,599	3,599
R^2	0.041	0.041	0.051	0.086

Table 4: **Univariate Analysis of AI Hedge Funds**

This table reports univariate comparisons of AI and non-AI hedge funds. The sample includes fund-month observations between 2006 and 2024 for USD-denominated U.S. hedge funds with at least \$5 million in assets. All variables are averaged to the fund level. Panel A shows average fund characteristics. Panel B shows average fund factor loadings. Fama-French factors are MKT, SMB, and HML for U.S. stock market, size, and value factors. Fung-Hsieh factors include SP500$-R_f$, Russell2000$-$SP500, Treasury Yield, Credit Spread, and PTFS Bond, PTFS FX, and PTFS Commodity, which are primitive trend-following factors that capture nonlinear exposures to bonds, foreign currencies, and commodities. AQR factors include excess returns of global Equity Indices, Fixed Income, and Commodity markets, and Value, Momentum, Carry, and Defensive, which are long-short style premia across all asset classes. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Fund Characteristics

Characteristic	AI	Non-AI	Difference	P-value
Quant	1.000	0.257	0.743***	0.000
Incentive Fee	18.467	16.017	2.450**	0.015
High Water Mark	0.872	0.860	0.012	0.786
Hurdle Rate	0.034	0.125	-0.091***	0.000
Lockup Period	2.121	4.990	-2.870***	0.000
Restriction Period	1.750	4.150	-2.401***	0.000
AUM	223.256	289.473	-66.217	0.548
Age	72.481	86.236	-13.755	0.204
Management Fee	1.397	1.414	-0.017	0.819

Panel B: Fund Return Factor Loadings

$\hat{\beta}$	AI	Non-AI	Difference	P-value
Fama-French Factors				
MKT	0.180	0.336	-0.156***	0.001
SMB	-0.017	0.079	-0.096**	0.017
HML	-0.067	0.010	-0.076**	0.025
Fung-Hsieh Factors				
SP500 - r_f	0.240	0.258	-0.018	0.682
Russell2000 - SP500	0.005	0.099	-0.094**	0.024
Treasury Yield	-0.005	-0.002	-0.003	0.618
Credit Spread	0.004	-0.022	0.027***	0.000
PTFS Bond	0.006	-0.002	0.008	0.217
PTFS FX	0.005	0.006	-0.001	0.873
PTFS Commodity	0.005	0.001	0.004	0.573
AQR Factors				
Equity Indices	0.192	0.322	-0.130***	0.006
Fixed Income	0.006	-0.054	0.060	0.531
Commodity	0.081	0.080	0.001	0.969
Value	-0.601	-0.283	-0.318**	0.016
Momentum	0.112	-0.141	0.253**	0.031
Carry	-0.314	0.045	-0.359***	0.006
Defensive	-0.075	0.280	-0.355***	0.004

Table 5: **Performance of AI Hedge Funds**

This table reports estimation results from regressing next-month hedge fund performance on current fund characteristics. The sample consists of fund-month observations between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI and Quant are indicator variables that equal one if the fund is classified as an AI fund and a quant fund in the current year, respectively. Year is the value of the current year minus 2006. Before 2017 equals one if the current month is before January 2018; After 2017 equals one if the current month is after December 2017. Incentive Fee and Management Fee are the incentive and management fees charged by the fund adviser. High Water Mark and Hurdle are indicator variables that equal one if the fund's compensation contract includes a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the fund's assets, and Age is its age. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh hedge fund factors in columns 1-3 and based on AQR multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Table 5: **Performance of AI Hedge Funds (Cont'd)**

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH			AQR		
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.084	0.871***		0.120	0.778***	
	(0.119)	(0.234)		(0.076)	(0.297)	
AI × Year		-0.059***			-0.049**	
		(0.021)			(0.022)	
AI × Before 2017			0.496***			0.488**
			(0.159)			(0.224)
AI × After 2017			-0.083			-0.029
			(0.119)			(0.120)
Quant	0.007	0.007	0.007	-0.035	-0.035	-0.034
	(0.040)	(0.040)	(0.040)	(0.043)	(0.043)	(0.043)
Incentive Fee	0.008***	0.007***	0.007***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High Water Mark	-0.065**	-0.064**	-0.064**	-0.050*	-0.050*	-0.049*
	(0.030)	(0.030)	(0.030)	(0.027)	(0.027)	(0.027)
Hurdle Rate	-0.035	-0.035	-0.035	-0.038	-0.038	-0.038
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Lockup Period	0.003*	0.003*	0.003*	0.003**	0.003**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Restriction Period	0.000	0.000	0.000	0.005*	0.005*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(AUM)	0.022***	0.022***	0.022***	0.017**	0.017**	0.017**
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Log(Age)	-0.024	-0.024	-0.025	-0.013	-0.013	-0.013
	(0.017)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)
Management Fee	0.039*	0.039*	0.039*	-0.012	-0.011	-0.011
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Strategy-Month FEs	Y	Y	Y	Y	Y	Y
N	324,952	324,952	324,952	324,952	324,952	324,952
R^2	0.114	0.114	0.114	0.116	0.116	0.116

Table 6: **Performance of Early and Late AI Adopters**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI is an indicator variable that equals one if the fund is classified as an AI fund in the current year. Early Adopter and Late Adopter are indicator variables that equal one if the fund's first year of using an AI-driven strategy is before January 2018 and after December 2017, respectively. Before 2017 and After 2017 are indicator variables that capture whether the current month is before January 2018 and after December 2017, respectively. Control variables are the same as in Table 5. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh hedge fund factors in column 1 and based on AQR multi asset class factors in column 2. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH	AQR
	(1)	(2)
AI × Early Adopter × Before 2017	0.497***	0.486**
	(0.160)	(0.223)
AI × Early Adopter × After 2017	0.076	-0.438**
	(0.257)	(0.219)
AI × Late Adopter × After 2017	-0.132	0.095
	(0.123)	(0.096)
Controls	Y	Y
Strategy-Month FEs	Y	Y
N	324,952	324,952
R^2	0.114	0.116

Table 7: **Performance of AI Hedge Funds Relative to Sibling Funds**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. The sample includes funds of hedge fund advisers with at least two funds in the month. AI is an indicator variable that equals one if the fund is classified as an AI fund in the current year. Year is the value of the current year minus 2006. Before 2017 and After 2017 are indicator variables that capture whether the current month is after December 2017. Control variables are the same as in Table 5. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh hedge fund factors in columns 1-3 and based on AQR multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH			AQR		
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.349**	1.076***		0.411**	1.338***	
	(0.148)	(0.181)		(0.202)	(0.413)	
AI × Year		-0.061***			-0.078**	
		(0.013)			(0.033)	
AI × Before 2017			0.500***			0.778***
			(0.182)			(0.205)
AI × After 2017			0.231			0.124
			(0.165)			(0.276)
Controls	Y	Y	Y	Y	Y	Y
Strategy-Month FEs	Y	Y	Y	Y	Y	Y
Adviser-Month FEs	Y	Y	Y	Y	Y	Y
N	191,271	191,271	191,271	191,271	191,271	191,271
R^2	0.677	0.677	0.677	0.677	0.677	0.677

Table 8: **Comovement of Hedge Fund Performance**

This table tests the comovement of AI hedge fund performance. Panel A reports average pairwise correlations of monthly alphas among fund pairs within the same HFR strategy category. For AI Pairs, correlations are computed using only months in which both funds are classified as AI; for Non-AI Pairs, only months in which both are non-AI. Each pair requires at least 12 overlapping months. Difference is the mean correlation of AI Pairs minus Non-AI Pairs, with t-statistics based on standard errors two-way clustered by each fund. Columns 1 and 3 include all fund pairs within the same strategy category; columns 2 and 4 exclude funds managed by the same adviser. Panel B reports regressions of monthly fund alpha on the Peer Performance, defined as average alpha of all funds in the same strategy-month (excluding the fund itself), and its interaction with the AI indicator. Columns 1 and 3 include all peers; columns 2 and 4 exclude peers managed by the same adviser. Controls include quant, incentive fee, high water mark, hurdle rate, lockup period, restriction period, log TNA, log age, and management fee. Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Average Pairwise Correlation

Factor Model:	FH		AQR	
	All Pairs	Exclude Siblings	All Pairs	Exclude Siblings
	(1)	(2)	(3)	(4)
AI Pairs	0.021	0.004	0.077	0.058
Non-AI Pairs	0.124	0.123	0.110	0.109
Difference	-0.103***	-0.119***	-0.033*	-0.051***
T-Statistic	-6.139	-8.580	-1.904	-3.119

Panel B: Regressions of Fund Performance on Peer Performance

Factor Model:	FH		AQR	
	All Peers	Exclude Siblings	All Peers	Exclude Siblings
	(1)	(2)	(3)	(4)
Peer Performance	0.463***	0.471***	0.535***	0.540***
	(0.070)	(0.059)	(0.067)	(0.054)
Peer Performance×AI	-0.124**	-0.139***	-0.123**	-0.144***
	(0.058)	(0.047)	(0.056)	(0.042)
AI	-0.003	-0.001	0.106	0.112
	(0.105)	(0.105)	(0.077)	(0.079)
Controls	Y	Y	Y	Y
N	324,952	324,952	324,952	324,952
R^2	0.071	0.070	0.083	0.080

Table 9: **Money Flows to AI Hedge Funds**

This table reports estimation results of regressing hedge fund flow in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI and Quant are indicator variables that equal one if the fund is classified as an AI fund and a quant fund in the current year, respectively. Performance is lagged 12-month rolling-window cumulative alpha based on Fung-Hsieh seven hedge fund factors. AUM is the fund's assets, and Age is its age. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. Management Fee is the management fee rate charged by the fund adviser. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Flow

	(1)	(2)	(3)	(4)
AI	0.195	-0.064	-0.032	-0.013
	(0.241)	(0.241)	(0.243)	(0.256)
Performance		0.345***	0.345***	0.346***
		(0.044)	(0.044)	(0.044)
Log(AUM)		0.028	0.028	0.024
		(0.017)	(0.017)	(0.016)
Log(Age)		-0.504***	-0.505***	-0.517***
		(0.051)	(0.051)	(0.046)
Quant			-0.054	0.009
			(0.057)	(0.055)
Incentive Fee				-0.005
				(0.005)
High Water Mark				-0.070
				(0.098)
Hurdle Rate				0.027
				(0.070)
Lockup Period				0.011***
				(0.004)
Restriction Period				0.031***
				(0.008)
Management Fee				-0.139**
				(0.054)
Strategy-Month FEs	Y	Y	Y	Y
N	319,840	319,840	319,840	319,840
R^2	0.024	0.033	0.033	0.034

Table 10: **Survivorship of AI Hedge Funds**

This table reports average dropout rates of AI and Non-AI hedge funds over 1-month, 3-month, 6-month, and 1-year time horizons. The sample period is between 2008 and 2024. Panel A presents dropout rates related to both fund liquidations and stopped reportings. Panels B and C separately present the rates of liquidations and stopped reportings, respectively. T-statistics from testing the difference between AI funds and non-AI funds are based on Newey-West standard errors with 12 monthly lags. All differences are statistically insignificant at the 10% level.

Panel A: Dropout Rate (%)

	1m	3m	6m	1y
AI Funds	1.882	5.470	10.627	19.625
Non-AI Funds	1.458	4.282	8.286	15.397
Difference	0.447	1.267	2.503	4.638
t-statistics	1.165	1.186	1.260	1.444

Panel B: Liquidation Rate (%)

	1m	3m	6m	1y
AI Funds	1.183	3.520	6.936	12.923
Non-AI Funds	0.827	2.423	4.686	8.710
Difference	0.362	1.117	2.296	4.374
t-statistics	1.023	1.094	1.176	1.336

Panel C: Stop Reporting Rate (%)

	1m	3m	6m	1y
AI Funds	0.699	1.949	3.691	6.703
Non-AI Funds	0.631	1.858	3.600	6.686
Difference	0.085	0.150	0.208	0.263
t-statistics	0.406	0.267	0.198	0.142

Internet Appendix

"The Growth and Performance of AI in Asset Management"

IA.1. Labor-Based Measures of Investment Adviser's AI Adoption

IA.1.1. AI-Related Job Postings

One measure of an investment adviser's AI adoption is constructed using the skills required for job positions, following the methodology in Babina, Fedyk, He, and Hodson (2024a) ("BFHH" henceforth). Specifically, we evaluate each job posting's relevance to AI and its core fields: machine learning (ML), natural language processing (NLP), and computer vision (CV), based on the skills extracted from online job postings.

For each skill s required in job postings, we calculate its relevance to AI as

$$w_s^{\mathrm{AI}} = \frac{\text{number of jobs requiring both core AI skills and skill } s}{\text{number of jobs requiring skill } s}, \tag{IA.1}$$

where a job is defined as requiring core AI skills if it has at least one of ML, NLP, CV, and AI in its required skills or job title. Next, we calculate the AI-relevance of a job posting j, w_j^{AI}, as the average of w_s^{AI} across all skills s required by the job posting j. Following BFHH, we define job posting j as AI-related if w_j^{AI} exceeds 0.1, a threshold chosen based on manual inspection of the data. Finally, we calculate our AI labor intensity measure $AI\%$ as the fraction of AI-related job postings by investment adviser i in year t. Figure IA.1 visualizes the top 100 skills ranked by their AI-relevance weight w_s^{AI}, and Figure IA.2 displays the top 100 most frequent skills among AI-related job postings.

IA.1.2. Alternative Classification of Job Postings

In addition to the BFHH measure, we also calculate an investment adviser's job postings related to AI following Abis and Veldkamp (2024) which we refer to as "AV" measure. Unlike the "BFHH" measure, which relies on the frequency of co-occurrence between a job posting's required skills and core AI skills, the AV measure classifies job postings into one of four categories: AI, old technology (OT), and data management (DM), or none, based on the relative frequency of keywords associated with AI, OT, or DM in the job description. For example, if a job posting contains nine AI-related phrases and ten DM-related phrases, the AV measure categorizes it as a DM post rather than an AI post.

The AV measure of AI-related job posting share is positively correlated with the BFHH measure and has a similar distribution. It has a mean close to 1%, a median of 0%, and its 75th and 90th percentiles are 0.18% and 2.06%, respectively. Table IA.1 examines the cross-sectional relationship between an investment adviser's fund composition and its share of AI-related job postings based on Abis and Veldkamp (2024). The estimation results are largely consistent with Table 3: AI labor intensity is strongly and positively correlated with managing private funds, and within private funds, it is positively correlated with the asset share of hedge funds.

IA.1.3. Measuring AI Adoption Using LinkedIn Profiles

Job postings reflect a firm's demand for new workers rather than its current employees. To test the robustness of the job-posting–based results in Table 3, we construct an alternative labor-based measure of investment adviser's AI adoption using their existing employees' LinkedIn profiles from Revelio Labs.

Unlike job postings, which are designed to recruit candidates for specific tasks and therefore provide detailed descriptions of responsibilities and required skills, LinkedIn profiles contain the user's self-reported experiences, such as past job positions. As a result, the job titles or descriptions tend to be brief and rarely specify AI-related skills or tasks, and it is difficult to directly apply the AI-skill or AI-keyword approaches used for job-posting data. To address this challenge, we follow the method in Cen, Han, Han, and Jo (2025) and use the share of employees in data-related occupations as a proxy for the share of AI-related employees.[1]

Table IA.2 reports summary statistics for investment advisers matched to LinkedIn profiles. This sample is larger than the adviser–job-posting sample because many smaller advisers are successfully linked to LinkedIn data but not to job postings. As a result, the average AUM in the LinkedIn-matched sample is about USD 26 billion, compared with USD 66 billion in the job-posting-matched sample. Table IA.3 reports the relation between an investment adviser's fund composition and its share of data-related employees in the following year. Again, consistent with Table 3, the data-related employee share is strongly and positively associated with managing private funds and within private funds, positively associated with only one fund category: hedge funds.

IA.2. Cross-Validation of Measured AI-Driven Investing

To validate our text-based AI classifications, we examine whether firms in Form ADV Part 2A and the HFR database that are classified as AI-driven hire more AI-related workers, using two independent labor market data sources: (i) the share of AI-related job postings from Lightcast, and (ii) the share of employees in data-related occupations from LinkedIn profiles (Revelio Labs). For each of the two firm-level AI classifications (i.e., the ADV Part 2A and HFR), we restrict to subsamples of adviser-years that also exist in the labor databases.

Table IA.4 reports the results. Panel A groups investment advisers by their AI disclosure category from Form ADV Part 2A, where we consider two categories of AI-driven investing AI-Autonomous and AI-augmented. Across both labor measures, AI-Autonomous advisers have the highest AI labor intensity, followed by AI-Augmented, non-AI Quant, and Non-

[1] Cen, Han, Han, and Jo (2025) consider three groups of data-related roles: data collection, data analytics, and data maintenance. The specific occupations include Data Scientists, Statisticians, Digital Forensics Analysts, Business Intelligence Analysts, Clinical Data Managers, Database Administrators, Database Architects, Information Security Analysts, Data Warehousing Specialists, Information Security Engineers, Penetration Testers.

Quant, exhibiting a monotonic pattern consistent with our classification hierarchy. Panel B groups HFR hedge fund advisers by whether they manage at least one AI-classified fund in the year. Advisers with AI funds have significantly higher shares of both AI-related job postings and data-related employees than advisers without AI funds.

IA.3. Which Hedge Fund Advisers Offer AI Funds?

The distinctiveness of AI hedge funds may reflect characteristics of their managing advisers. To assess the role of advisers in the growth of AI funds, we examine the relationship between adviser characteristics and the creation of AI hedge funds. Specifically, we regress the number of AI funds an adviser manages next year on the characteristics of its existing hedge funds. Because the dependent variable includes a large number of zero-valued observations, we estimate Poisson regressions with year fixed effects. Table IA.6 shows that, controlling for the size and age of existing funds, advisers facing stronger performance incentives are more likely to launch new AI funds and adopt AI in existing funds.

First, incentive fees are positively and significantly associated with the number of AI funds across all specifications. In Column (3), a one percentage point increase in the average incentive fee is associated with an 11.5% increase in the expected number of AI funds managed in the following year ($e^{1\times 0.109} - 1 \approx 0.115$). This suggests that greater pay-for-performance sensitivity incentivizes the adviser to improve fund performance by adopting new technologies.

Second, the fractions of funds with high water mark and hurdle rate provisions are negatively associated with the number of AI funds. One potential explanation is that these provisions make the fee structures resemble out-of-the-money options, thereby reducing the sensitivity of manager compensation to performance and discouraging managers from investing in AI technology.

Third, the liquidity an adviser provides to its existing fund investors is also positively associated with the number of AI funds. Offering shorter lockup and restriction periods imposes implicit incentives to deliver better performance (Agarwal, Daniel, and Naik, 2009). Such investor-friendly contractual terms also require liquidity management skills, suggesting that advisers with such expertise are more likely to manage AI funds.

IA.4. Prompts for Processing Textual Data

IA.4.1. Form ADV Part 2A

We classify each adviser's Item 8 disclosure into one of five AI categories using the following prompt with OpenAI's GPT-5 model. The input text is the extracted Item 8 section from the adviser's Part 2A filing.

Classify this investment adviser's AI/ML usage based on their Form ADV Part 2A (Item 8) disclosure. Extract the following details:

1. **AI category.** Classify the adviser's AI usage into one of the following categories: **AI-Autonomous**: AI/ML is the primary investment decision-making engine—the strategy would not exist without AI/ML (e.g., fully systematic ML-driven trading, autonomous AI trading systems). **AI-Augmented**: AI/ML is a significant input to investment decisions, but humans retain final decision-making authority (e.g., ML generates buy/sell signals that a portfolio manager reviews; NLP extracts sentiment used alongside fundamental analysis). **AI Support**: The adviser uses AI/ML for research support or operational tasks that do not directly inform specific investment decisions—data extraction, dataset cleaning, report generation, compliance monitoring, client communication, back-office automation. **AI-Theme Assets**: The adviser invests in AI-themed stocks or AI-sector companies. The AI mention is about the investee companies, not about the adviser's own process. **AI Risk Disclosure**: AI is mentioned only in risk disclosures or disclaimers.

2. **Is quantitative?** Does the adviser use mathematical models, statistical techniques, algorithmic trading, systematic approaches, or any quantitative methodology as a core part of investment decisions? Any adviser using AI/ML for investment decisions (AI-Autonomous or AI-Augmented) is inherently quantitative. Answer **Y** or **N**.

Separately, we classify filings containing quantitative keywords using a similar prompt with OpenAI's GPT-5-mini model to identify advisers employing quantitative investment strategies.

IA.4.2. HFR Fund Strategy Descriptions

Please read the following text from a fund strategy description. Extract the following details, each on a new line:

1. Does the fund use **Artificial Intelligence (AI)**? Answer **Y** only if the description explicitly mentions AI technologies terms such as machine learning, deep learning, neural network, natural language processing, genetic algorithm, evolutionary computation, or reinforcement learning, or directly states that models self-learn or adapt automatically over time from big data. Do not infer AI usage from general terms like quantitative, systematic, algorithmic, predictive models, technical analysis, or statistical models unless paired with one of the AI terms above. Answer **N** for general quantitative, systematic, or algorithmic strategies, statistical objectives, proprietary formulas, or technical indicators that do not learn from data, or rules-based systems without adaptation. Answer N for pattern recognition not explicitly linked to machine learning, neural networks, or other adaptive AI methods. Answer only **Y**, **N**, or Borderline.

2. Does the fund use a **quantitative strategy** (regardless of AI)? Answer **Y** only if there is evidence of mathematical models, statistical techniques, algorithmic trading, or systematic approaches used in investment decisions. Discretionary, fundamental, or human-driven strategies should be marked **N**. Answer **Y** or **N**.

IA.5. Examples of Classified Investment Strategies

IA.5.1. Examples of AI classifications in Form ADV Part 2A

AI-Autonomous. *Ultra Blue Capital, LLC*: “Predictions and resultant investment decisions are based on detailed fundamental analysis performed by the supervised machine-learning algorithms. Using these patterns and other key metrics, our machines actively and automatically invest, divest, rebalance, and hedge.”

AI-Augmented. *Bristol Gate Capital Partners Inc*: “We have developed a proprietary machine learning model that uses the LightGBM python package to forecast the coming 12 months’ dividend growth for the S&P500® stocks or stocks traded on the TSX.” “We focus our fundamental research efforts (described below) on the top 65 predicted dividend growers in the US and top 55 predicted dividend growers in Canada.”

AI Support. *Brown Advisory LLC*: “Brown Advisory utilizes a proprietary application based on a large language model that enables members of the Institutional investment research team to query a database of publicly available documents and other research pertaining to issuers and companies and receive, in turn, a relevant summary of such documents. This application is designed to increase the efficiency of the research process but will not supplant Brown Advisory’s bottom-up investment research conducted by a team of professionals.”

IA.5.2. Examples of non-AI quantitative strategies in Form ADV Part 2A

Principal Street Partners, LLC: “PSP utilizes a proprietary screening and factor model to identify companies with very high quality and liquid balance sheets, durable cash flows, sensible dividend policy, dividend growth potential and that are trading at attractive relative valuations.”

Parametric Portfolio Associates LLC: “Parametric utilizes structured mathematical and rules-based methods of analysis. Parametric has designed proprietary models and technology that guide its investment decision-making processes."

First Quadrant, LP: "Our investment management process is generally model-driven and systematically implemented under the oversight of our portfolio management team." "We rely on our fundamental insights into markets and economies as the source of our ideas. The proprietary models we build are the systematic expression of those fundamental ideas."

IA.5.3. An example of AI hedge fund strategy description in HFR

Millburn Multi-Markets Program's ('MMM') core focus is to seek to provide investors with positive absolute returns through a variety of market cycles and environments, through diversified exposure to a range of liquid global markets and with an emphasis on rigorous risk management. MMM implements a group of models that collectively trade more than 100 futures, forward and spot contracts on currencies, interest rate instruments, stock indices, metals, energy and agricultural commodities, targeting opportunities in a wide range of global markets under a variety of conditions. Trade implementation takes place on U.S. and international exchanges and in the interbank currency market. Positions in each instrument traded can be either long or short, providing opportunities in both rising or falling markets.

MMM's trading strategies are based on the implementation of a multi-data-input, statistical/machine learning framework, and are 100% systematic and quantitative in nature. This framework utilizes price, price-derivative, and non-price data sources or 'features' in an attempt to provide an informed, context-specific and continuous view of portfolio positioning (long or short, and to what extent) in a particular market. Features/data inputs utilized in the construction of these trading models are generally intuitive, understandable and observable. MMM's statistical/machine learning approaches can enable the models to adapt over time, with the goal of reflecting underlying structural properties of markets and the importance of particular features during a range of market conditions.

Strategies are intended to be able to detect and take advantage of longer-term, persistent trending activity (up or down), but also short-term or idiosyncratic market behavior. Risks of over-fitting to recent data are reduced through the careful application of techniques, a focus on diversification and the use of often decades of historic data in the construction of the models. MMM covers themes that Millburn believes are capable of generating positive absolute returns including: the strength or weakness of global economies, changing currency values, rising or falling global interest rates and equities, and the changing prices of many essential commodities.

IA.5.4. Examples of non-AI quantitative strategies in HFR

Acadian Algorithmic Equity: "The algorithmic equity strategy does not use statistical estimation or machine learning but instead relies on first principles and investment insights. The strategy differs from a traditional fundamental approach in that it has automated much of the analysis that a fundamental analyst would perform."

Oak Park Market Neutral Partners: "100% quantitative - Fixed, equal number of long and short positions." "Fixed system: no self-training, no AI, no neural network, etc. Constantly reviewed, occasionally modified, but not self-modifying."

Ellington Quantitative Equity Partners: "The fund utilizes forecasts from over a dozen proprietary algorithms that rely on economic principles rather than pattern recognition or data mining."

ZAR Equity Market Neutral Fund: "Screening from a universe of over 4500 individual and ADR securities, stringent equity selection is incorporated via a systematic, fundamental equity selection model. The model identifies and ranks long and short candidates based on price to intrinsic valuation, earnings growth, volatility, and price momentum."

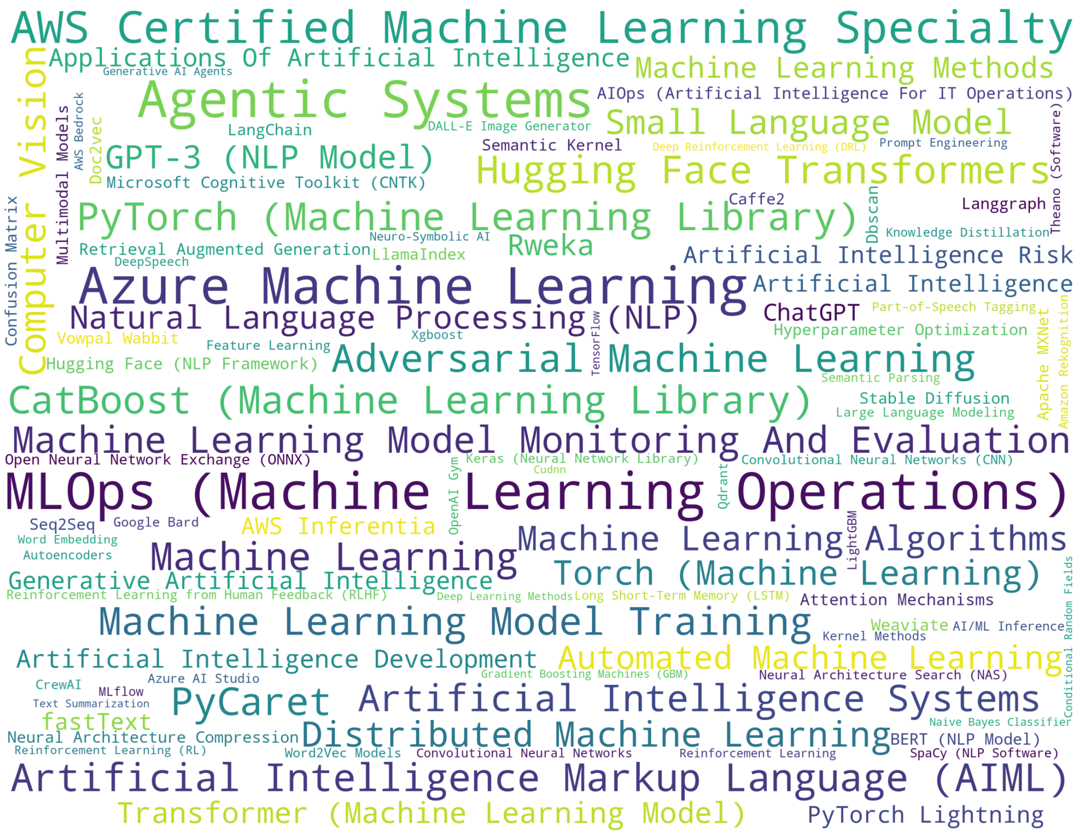


Figure IA.1: **Top 100 Skills with the Highest $w_s^{\mathbf{AI}}$.**
This figure shows the top 100 skills from job postings ranked by their AI relevance score, w_s^{AI}. The AI relevance score for a given skill (w_s^{AI}) measures how frequently this skill co-occurs with core AI skills. Specifically, it is calculated as: $w_s^{\text{AI}} = \frac{\text{Number of job postings requiring both core AI skills and skill } s}{\text{Number of job postings requiring skill } s}$. A job posting is considered to require core AI skills if it explicitly mentions at least one of the following terms: machine learning (ML), natural language processing (NLP), computer vision (CV), or artificial intelligence (AI), either among its required skills or in the job title. In this figure, skills with higher values of w_s^{AI} appear in larger fonts.

Figure IA.2: **Top 100 Most Frequent Skills in AI Job Postings by Investment Advisers.**

This figure presents the 100 most frequently required skills in AI-related job postings by registered investment advisers. A job posting j is classified as AI-related if the average AI relevance score (w_j^{AI}) across its required skills exceeds 0.1. Skills that occur more frequently are displayed in larger fonts.

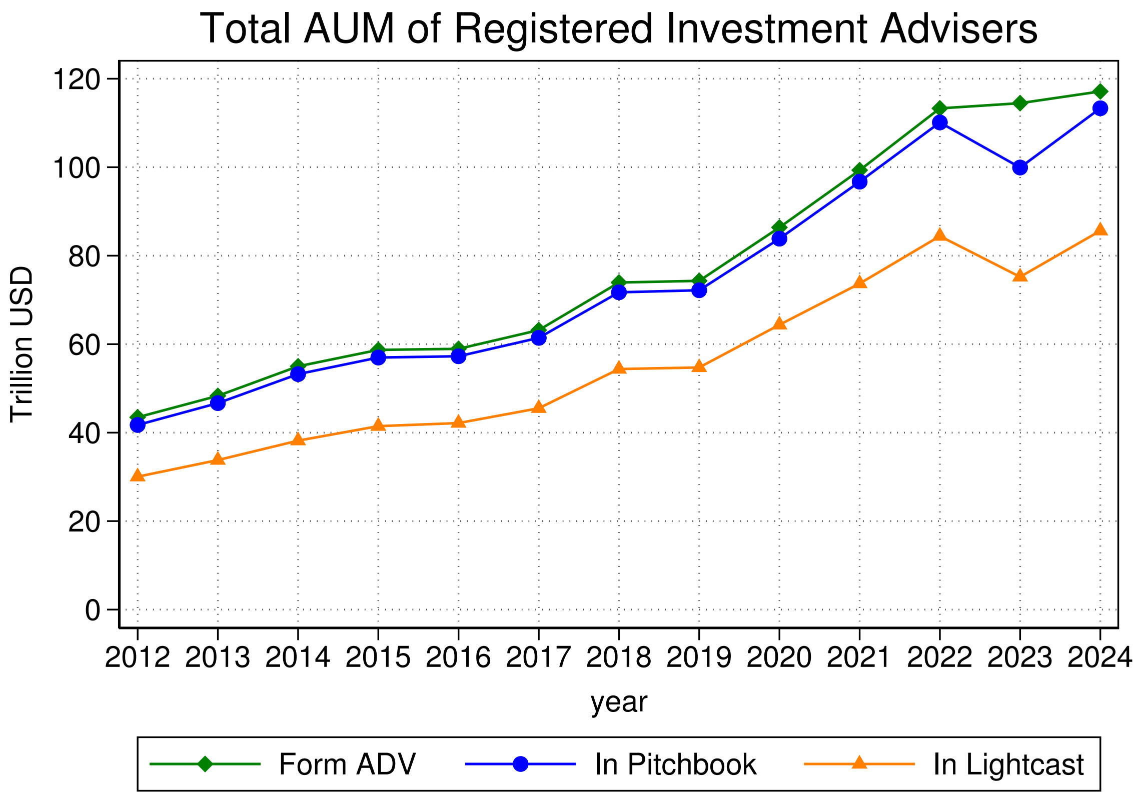


Figure IA.3: **Total AUM of Investment Advisers.**
This figure presents the total assets under management (AUM) of three sets of registered investment advisers. The green line indicates all investment advisers that file Form ADV. The blue line indicates the subset of investment advisers that are matched with companies in Pitchbook. The orange line indicates investment advisers matched to job postings in Lightcast.

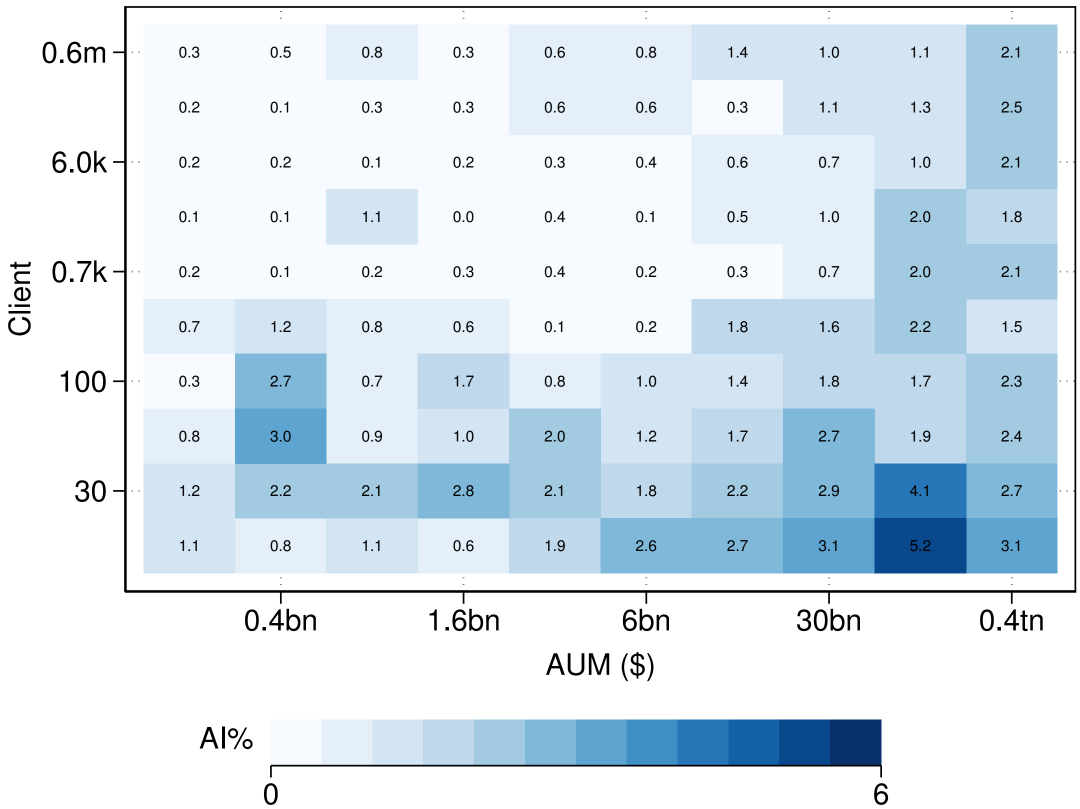


Figure IA.4: **Investment Adviser's AUM, Number of Clients, and AI Investment.** This figure presents the relationship between an investment adviser's current total AUM, the current total number of clients, and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. In each year, advisers are grouped into 10×10 bins sequentially by AUM and by the number of clients. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in the horizontal axis indicate the approximate average AUM in each of the ten AUM group bins, and labels in the vertical axis indicate the approximate average number of clients in each of the ten client number bins.

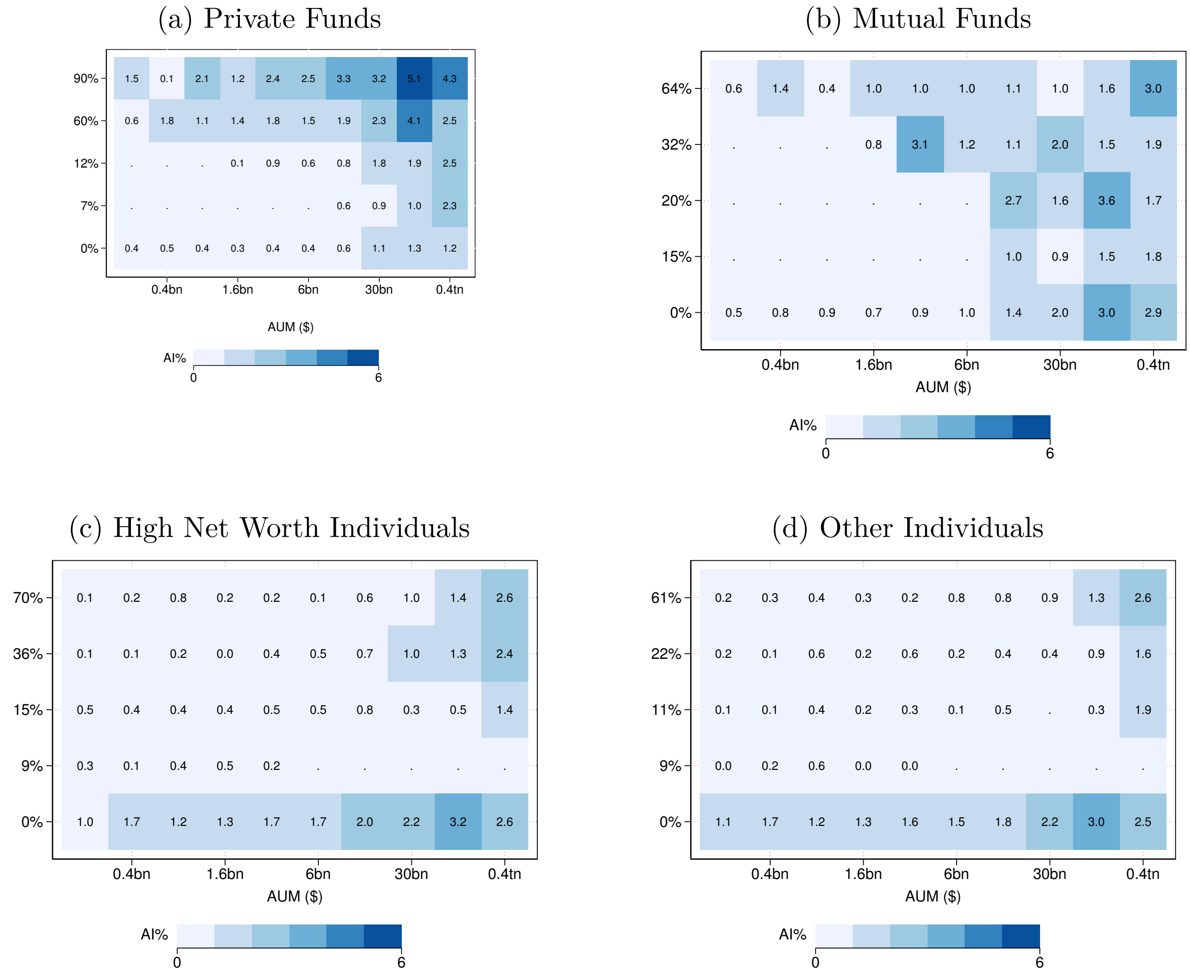


Figure IA.5: **Investment Adviser's AUM Composition and AI Investment.**
This figure presents the relationship between the composition of an investment adviser's current AUM and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels A-D focus on the fraction of AUM in the four largest groups of clients: private funds (i.e., pooled investment vehicles), mutual funds (i.e., registered investment companies), high-net-worth individuals, and other individuals, respectively. In each year, advisers are grouped into 10×5 bins sequentially by AUM and by the percentage of AUM in a client type. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in horizontal axes indicate the approximate average AUM in each of the ten AUM group bins, and labels in vertical axes indicate the approximate average percentage of AUM in each of the five client type bins.

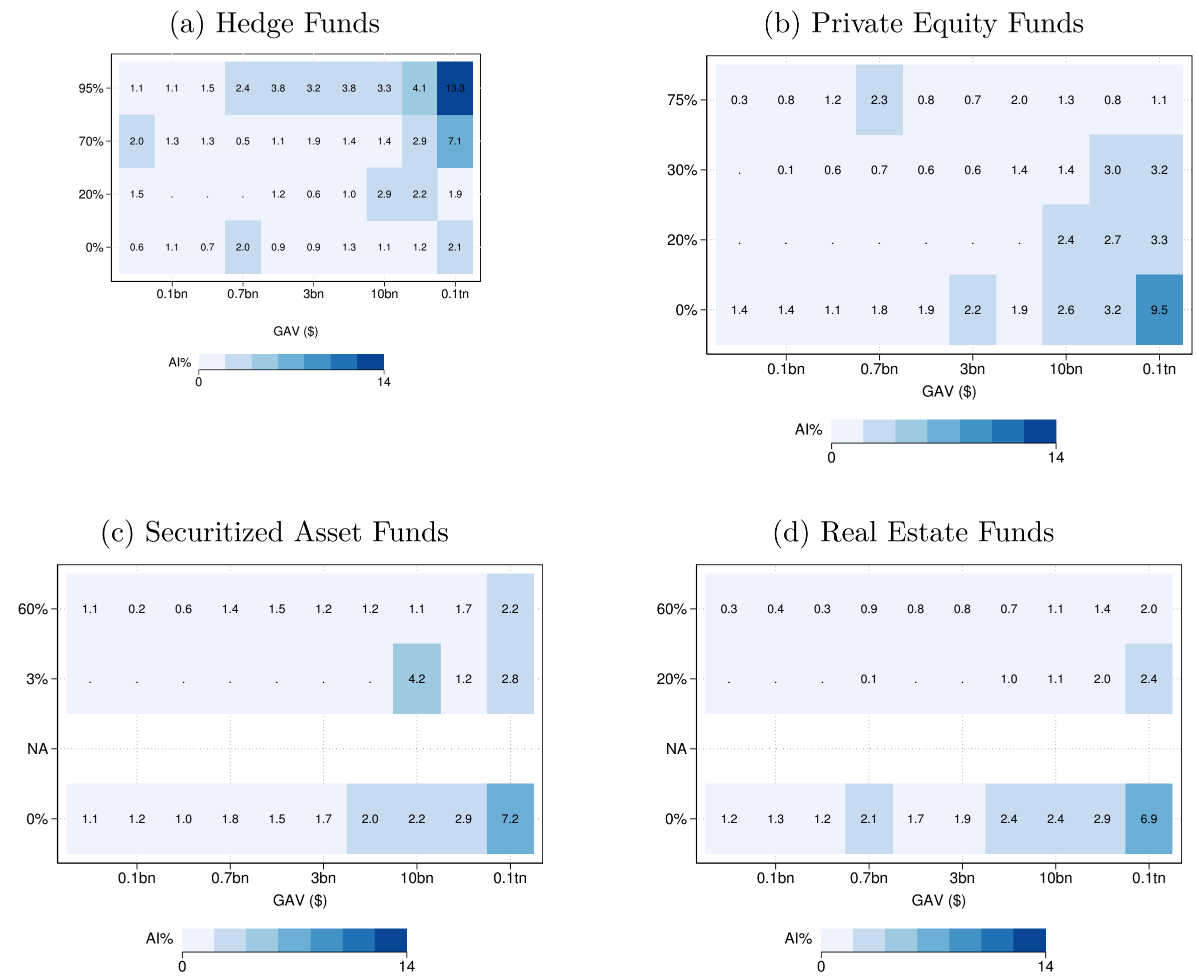


Figure IA.6: **Investment Adviser's Private Funds Composition and AI Investment.** This figure presents the relationship between the composition of an investment adviser's current private fund gross asset value (GAV) and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels A-D focus on the fraction of GAV in the four largest groups of private funds: hedge funds, private equity funds, securitized asset funds, and real estate funds, respectively. In each year, advisers are grouped into 10×4 bins sequentially by total GAV and by the percentage of GAV in a private fund group. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in horizontal axes indicate the approximate average GAV in each of the ten GAV group bins, and labels in vertical axes indicate the approximate average percentage of GAV in each of the four fund group bins.

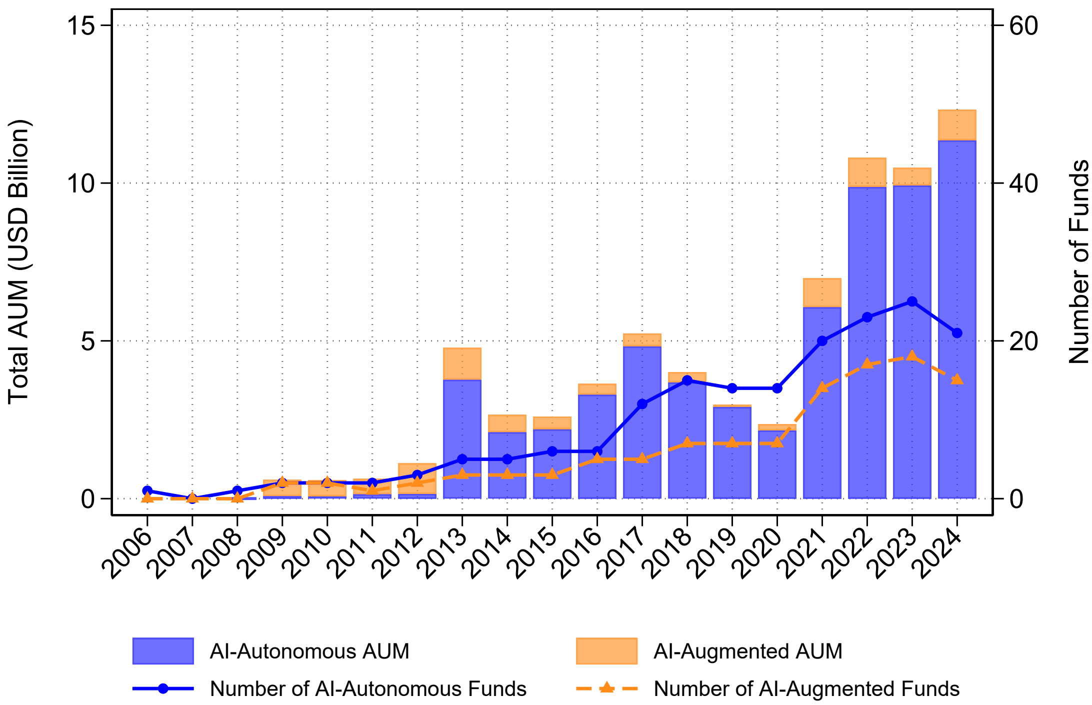
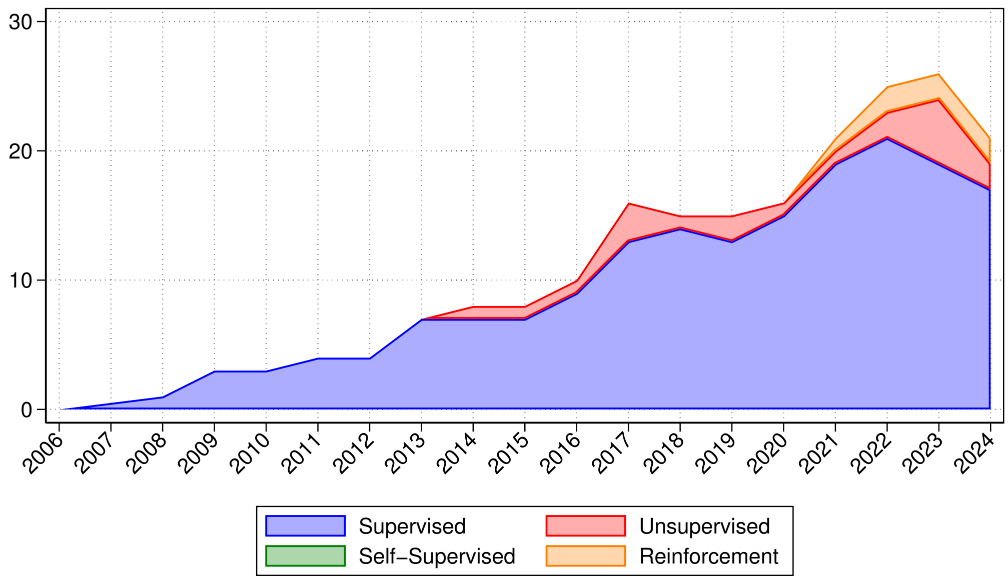


Figure IA.7: **The Growth of AI Hedge Funds: AI-Autonomous and AI-Augmented.** This figure presents the growth of AI hedge funds between 2006 and 2024, separately for AI-Autonomous and AI-Augmented strategies. Lines show the number of hedge funds by year, and stacked bars show their total AUM by year.

(a) Learning Paradigms



(b) Model Approaches

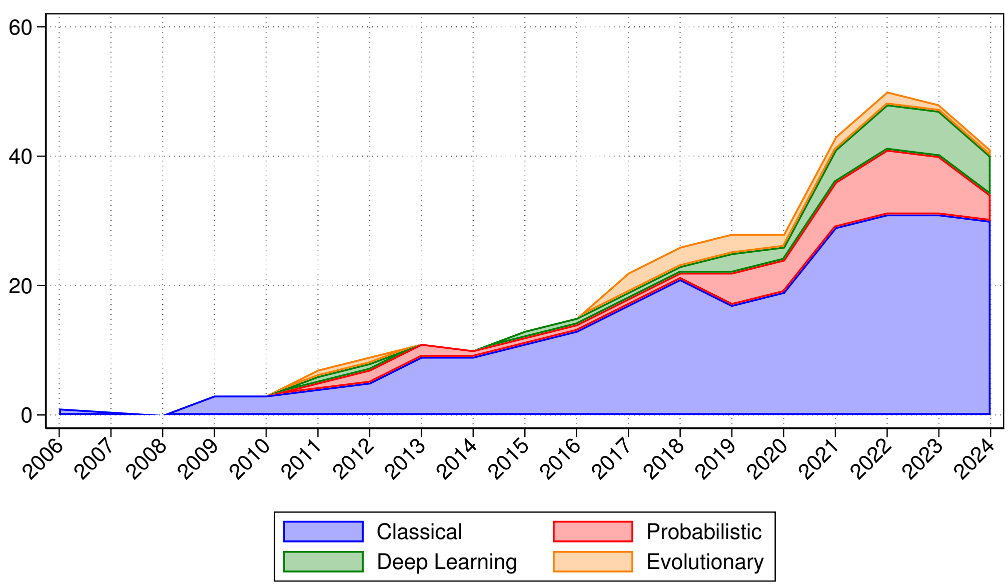
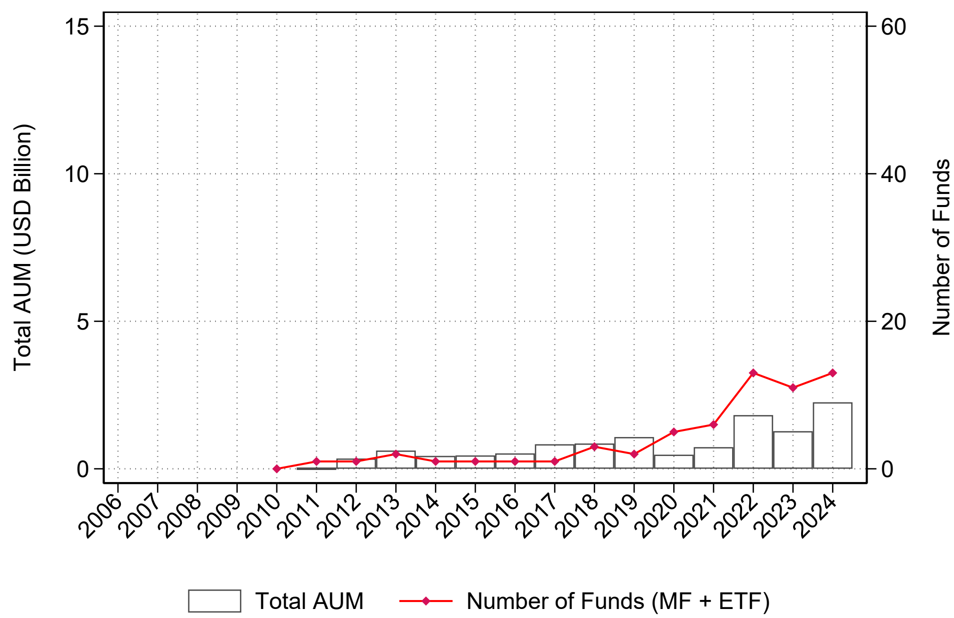


Figure IA.8: **AI Techniques of Hedge Funds.**
This figure presents AI learning paradigms and model approaches among U.S. hedge funds. Stacked areas represent the number of funds by year. Classifications are not mutually exclusive.

(a) Number and AUM of Mutual Funds



(b) Percentage of Mutual Funds

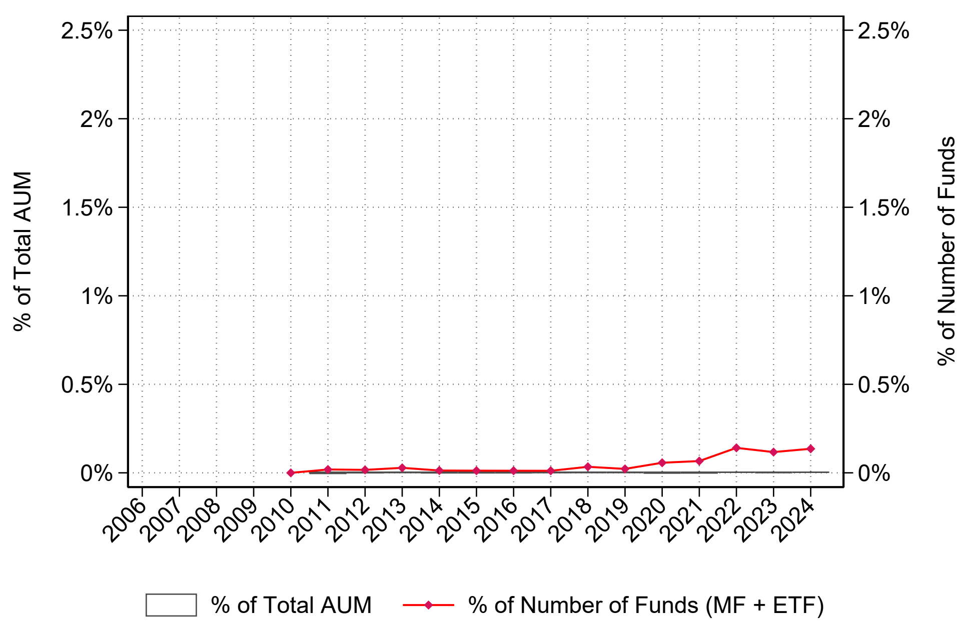
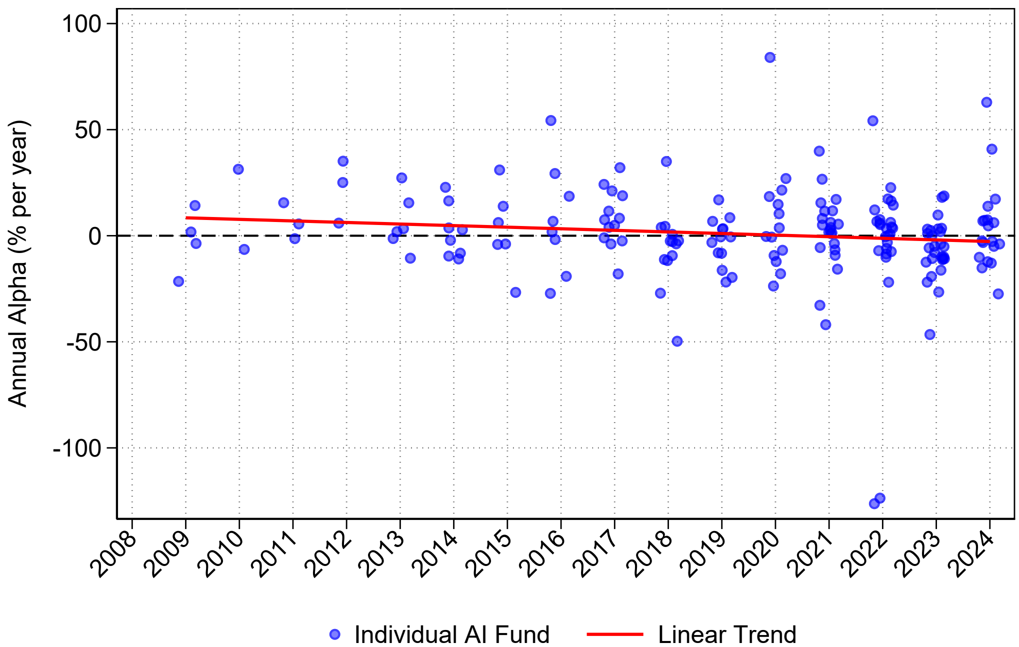


Figure IA.9: **The Growth of AI Mutual Funds.**
This figure presents the growth of AI mutual funds (including ETFs). We identify AI mutual funds by processing investment strategy descriptions in Form 497K with the same GPT-5 model and prompt. Panel A shows the number and total AUM of AI mutual funds by year. Panel B shows their number and total AUM as percentages of all open-ended mutual funds in the SEC Form 497K and CRSP database. The horizontal and vertical axes are kept the same as in Figure 3.

(a) Fung-Hsieh Alpha



(b) AQR Alpha

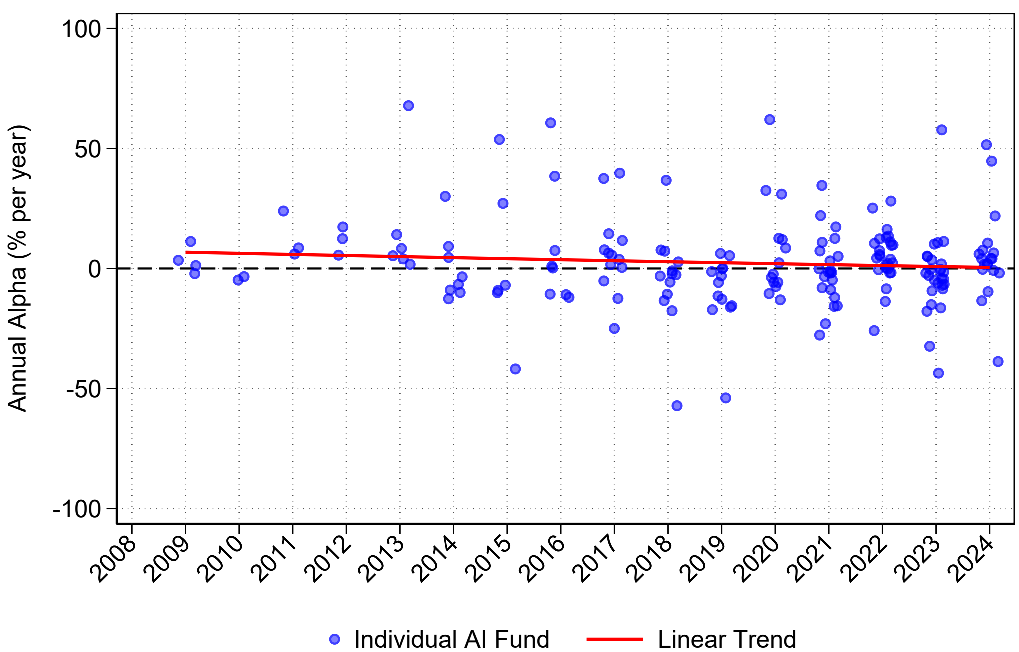


Figure IA.10: **Annual Alpha of Individual AI Hedge Funds.**
This figure presents scatterplots where each dot represents the annualized alpha of an individual AI fund in a given year. The red line shows the linear trend. Panel A uses Fung-Hsieh alpha; Panel B uses AQR alpha. Two cryptocurrency funds (Pantera Digital Asset Fund and Blockforce Capital Multi-Strategy Fund) have annual FH alphas exceeding -100% in 2022. Dots are shifted horizontally by up to ±0.2 years for visibility; the linear trend uses the original year.

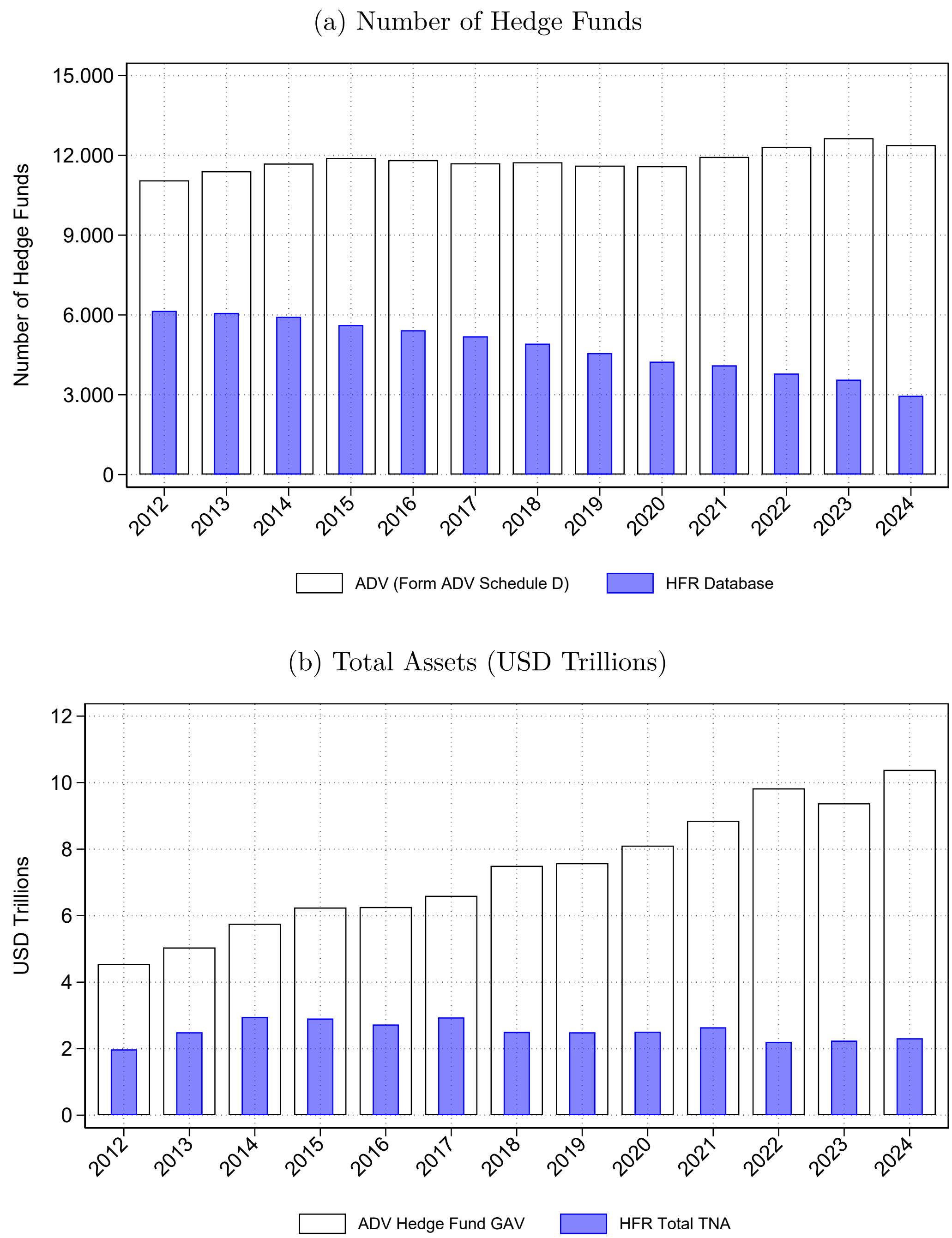


Figure IA.11: **Hedge Fund Coverage: Form ADV vs. HFR Database.**
This figure compares the number and total assets of hedge funds reported in SEC Form ADV (Schedule D, Section 7B(1)) and the HFR database between 2012 and 2024. Panel A shows the number of hedge funds. Panel B shows total gross asset value (ADV) and total net assets (HFR) in USD trillions.

Table IA.1: **Investment Adviser's Fund Composition and AI Job Postings ("AV" measure)**

This table reports results from regressing the percentage of the investment adviser's AI-related jobs among its job postings in the next year, measured following Abis and Veldkamp (2024), on the current size and composition of its assets. Every observation represents an adviser-by-year between 2012 and 2023 with at least $100 million of current AUM and at least 5 job posts in the next year. Panel A uses the adviser's total assets under management (AUM), and the sample includes all adviser-years. AUM is the total regulatory assets under management. Account is the adviser's total number of managed accounts. Advise Private Fund is an indicator variable that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. Panel B uses the adviser's private fund gross asset values (GAVs), and the sample includes only adviser-years that manage private funds. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: AI% Job Postings, All Investment Advisers

	(1)	(2)	(3)	(4)
log(AUM)	0.115**	0.171***	0.110*	0.101**
	(0.046)	(0.055)	(0.056)	(0.048)
log(Account)		-0.144***	-0.101***	
		(0.044)	(0.039)	
Advise Private Fund			0.657***	
			(0.175)	
AUM% Discretionary				0.005*
				(0.003)
AUM% Private Fund				0.013***
				(0.005)
AUM% Mutual Fund				-0.003
				(0.002)
AUM% HighNetWorth				-0.011***
				(0.004)
AUM% Individual				0.005
				(0.007)
Year FEs	Y	Y	Y	Y
N	7,646	7,646	7,646	7,646
R^2	0.015	0.023	0.026	0.034

Table IA.1: **Investment Adviser's Fund Composition and AI Job Postings ("AV" measure, Cont'd)**

Panel B: AI% Job Postings, Advisers of Private Funds

	(1)	(2)	(3)	(4)
log(GAV)	0.257***	0.295***	0.407***	0.355***
	(0.067)	(0.074)	(0.118)	(0.102)
log(AUM)		-0.090		
		(0.081)		
log(Number of Private Fund)			-0.363*	-0.280
			(0.187)	(0.173)
GAV% Hedge Fund				0.010
				(0.007)
GAV% Private Equity Fund				-0.006
				(0.004)
GAV% Real Estate Fund				-0.009**
				(0.004)
GAV% Securitized Asset Fund				-0.004
				(0.005)
GAV% Venture Capital Fund				0.017
				(0.012)
Year FEs	Y	Y	Y	Y
N	3,599	3,599	3,599	3,599
R^2	0.030	0.030	0.033	0.044

Table IA.2: **Summary Statistics: SEC Registered Investment Advisers Linked with LinkedIn Profiles**

This table presents summary statistics for the sample of investment advisers linked with LinkedIn Profiles. Every observation is an adviser-year between 2012 and 2024 with at least $100 million of current AUM and at least 5 job posts. Data% Employees is the percentage of data-related positions among the adviser's employees. AUM is the adviser's total regulatory assets under management in billion USD. Account is the adviser's total number of managed accounts in thousands. Advise Private Fund is an indicator variable that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. GAV is the adviser's total private fund gross asset values in billion USD. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category.

	N	mean	sd	p10	p25	p50	p75	p90
Data% Employees	87,223	3.14	5.13	0.00	0.00	0.00	5.02	9.38
AUM	87,223	26.16	174.79	0.16	0.30	0.81	3.45	20.46
Account	87,223	19.06	214.11	0.00	0.01	0.25	1.12	3.72
Advise Private Fund	87,223	0.45	0.50	0.00	0.00	0.00	1.00	1.00
AUM% Discretionary	87,223	88.35	24.77	55.40	92.05	100.00	100.00	100.00
AUM% Private Fund	87,223	30.80	41.69	0.00	0.00	0.00	87.50	100.00
AUM% Mutual Fund	87,223	8.00	22.96	0.00	0.00	0.00	0.00	26.64
AUM% HighNetWorth	87,223	28.31	33.13	0.00	0.00	12.50	62.10	84.49
AUM% Individual	87,223	15.41	23.71	0.00	0.00	0.47	21.53	55.07
GAV	87,223	1.76	10.15	0.00	0.00	0.00	0.47	2.62
Number of Private Fund	87,223	4.95	16.86	0.00	0.00	0.00	4.00	12.00
GAV% Hedge Fund	39,154	41.18	46.65	0.00	0.00	0.90	100.00	100.00
GAV% Private Equity Fund	39,154	31.36	43.99	0.00	0.00	0.00	97.84	100.00
GAV% Real Estate Fund	39,154	7.65	25.35	0.00	0.00	0.00	0.00	6.50
GAV% Securitized Asset Fund	39,154	2.86	14.64	0.00	0.00	0.00	0.00	0.00
GAV% Venture Capital Fund	39,154	3.05	15.62	0.00	0.00	0.00	0.00	0.00

Table IA.3: **Investment Adviser's Fund Composition and Data-related Employees**

This table reports results from regressing the percentage of the investment adviser's data-related employees among all its employees in the next year on the current size and composition of its assets. Every observation represents an adviser-by-year between 2012 and 2023 with at least $100 million of current AUM and at least 5 employees in the next year. Panel A uses the adviser's total assets under management (AUM), and the sample includes all adviser-years. AUM is the total regulatory assets under management. Account is the adviser's total number of managed accounts. Advise Private Fund is an indicator variable that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. Panel B uses the adviser's private fund gross asset values (GAVs), and the sample includes only adviser-years that manage private funds. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Data% Employees, All Investment Advisers

	(1)	(2)	(3)	(4)
log(AUM)	0.693***	0.789***	0.740***	0.511***
	(0.053)	(0.046)	(0.046)	(0.062)
log(Account)		-0.339***	-0.275***	
		(0.035)	(0.036)	
Advise Private Fund			0.569***	
			(0.138)	
AUM% Discretionary				0.003
				(0.002)
AUM% Private Fund				0.002
				(0.002)
AUM% Mutual Fund				0.006
				(0.004)
AUM% HighNetWorth				-0.021***
				(0.002)
AUM% Individual				-0.021***
				(0.004)
Year FEs	Y	Y	Y	Y
N	78,214	78,214	78,214	78,214
R^2	0.074	0.109	0.110	0.110

Table IA.3: **Investment Adviser's Fund Composition and Data-related Employees (Cont'd)**

Panel B: Data% Employees, Advisers of Private Funds

	(1)	(2)	(3)	(4)
log(GAV)	0.286***	0.081**	0.482***	0.365***
	(0.042)	(0.040)	(0.060)	(0.049)
log(AUM)		0.448***		
		(0.069)		
log(Number of Private Fund)			-0.579***	-0.144
			(0.147)	(0.116)
GAV% Hedge Fund				0.008***
				(0.003)
GAV% Private Equity Fund				-0.028***
				(0.003)
GAV% Real Estate Fund				-0.011
				(0.010)
GAV% Securitized Asset Fund				-0.002
				(0.006)
GAV% Venture Capital Fund				-0.017***
				(0.005)
Year FEs	Y	Y	Y	Y
N	35,116	35,116	35,116	35,116
R^2	0.017	0.036	0.025	0.089

Table IA.4: **Cross-Validation of AI Classification Using Labor Data**

This table presents a cross-validation of our text-based AI classifications using Form ADV Part 2A, the HFR database, and two independent labor market measures. Panel A groups investment advisers by their AI disclosure category from Form ADV Part 2A. Panel B groups HFR hedge fund advisers by whether they manage at least one AI-classified fund. Under "Job Postings", column "N" reports the number of adviser-years that are in both Form ADV Part 2A (or HFR), and column "AI%" reports the mean share of AI-related job postings from Lightcast. Under "LinkedIn", column "N" reports the number of adviser-years that are in both Form ADV Part 2A (HFR) and LinkedIn, and column "Data%" reports the mean share of employees with LinkedIn profiles in data-related occupations from Revelio Labs.

Panel A: Investment Advisers in ADV Part 2A

	Job Postings		LinkedIn	
	N	AI%	N	Data%
AI-Autonomous	8	10.1%	40	8.4%
AI-Augmented	57	4.8%	98	4.6%
non-AI Quant	2,470	3.4%	6,615	3.6%
Non-Quant	11,131	0.7%	52,610	2.6%

Panel B: Hedge Fund Advisers in HFR

	Job Postings		LinkedIn	
	N	AI%	N	Data%
Has AI Funds	9	25.4%	42	8.2%
No AI Funds	910	2.1%	4,870	4.6%

Table IA.5: **Performance of AI Hedge Funds: AI-Autonomous and AI-Augmented**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI-Autonomous is an indicator variable that equals one if AI/ML is the primary decision-making engine of the fund's strategy in the current year; AI-Augmented is an indicator variable that equals one if AI/ML is a significant input combined with fundamental or other quantitative methods. Year is the value of the current year minus 2006. Before 2017 and After 2017 are indicator variables that capture whether the current month is before January 2018 and after December 2017, respectively. Control variables are the same as in Table 5. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh hedge fund factors in columns 1-3 and based on AQR multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH			AQR		
	(1)	(2)	(3)	(4)	(5)	(6)
AI-Autonomous	0.195	0.939***		0.161	1.196***	
	(0.152)	(0.352)		(0.107)	(0.384)	
AI-Autonomous × Year		-0.055*			-0.077***	
		(0.030)			(0.029)	
AI-Autonomous × Before 2017			0.741***			0.797***
			(0.202)			(0.262)
AI-Autonomous × After 2017			0.002			-0.062
			(0.138)			(0.160)
AI-Augmented	-0.144	0.759*		0.035	0.245	
	(0.123)	(0.422)		(0.135)	(0.239)	
AI-Augmented × Year		-0.069**			-0.016	
		(0.033)			(0.021)	
AI-Augmented × Before 2017			0.112			0.000
			(0.155)			(0.135)
AI-Augmented × After 2017			-0.279			0.051
			(0.175)			(0.194)
Controls	Y	Y	Y	Y	Y	Y
Strategy-Month FEs	Y	Y	Y	Y	Y	Y
N	324,952	324,952	324,952	324,952	324,952	324,952
R^2	0.114	0.114	0.114	0.116	0.116	0.116

Table IA.6: **Adviser Characteristics and the Number of AI Hedge Funds**

This table reports Poisson regressions of a hedge fund adviser's number of AI funds in the next year on its current fund characteristics. Every observation is a hedge fund adviser-year between 2006 and 2024 with at least $5 million of hedge fund AUM. Incentive Fee and Management Fee are the average incentive and management fee rates charged by the adviser's hedge funds. High Water Mark and Hurdle Rate are the fractions of the adviser's hedge funds whose compensation contracts include high water mark and hurdle rate provisions, respectively. Lockup Period is the minimum number of months that investors must wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the adviser's total hedge fund assets under management. Age is the adviser's maximum fund age. Return is the average annual return of the adviser's funds during the current year. In columns 1-3, all funds are included, and independent variables are equally weighted across the adviser's funds. In columns 4-6, only funds that consistently report monthly AUM are included, and independent variables are weighted by fund AUM. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Number of AI Hedge Funds

	Equal-Weighted			AUM-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive Fee	0.094***	0.103***	0.109***	0.090**	0.103***	0.119***
	(0.036)	(0.038)	(0.032)	(0.036)	(0.036)	(0.034)
High Water Mark	-1.741***	-0.825	-0.275	-1.679***	-0.817*	-0.520
	(0.442)	(0.512)	(0.562)	(0.432)	(0.479)	(0.501)
Hurdle Rate	-2.859**	-2.141*	-2.425	-2.362**	-1.641	-1.866
	(1.242)	(1.136)	(1.491)	(1.176)	(1.002)	(1.204)
Lockup Period		-0.054	-0.051		-0.037	-0.042
		(0.045)	(0.046)		(0.042)	(0.044)
Restriction Period		-0.592***	-0.552***		-0.660***	-0.611***
		(0.135)	(0.141)		(0.125)	(0.127)
Log(Number of Funds)			1.065***			0.972***
			(0.162)			(0.215)
Log(Age)			-0.921**			-1.052***
			(0.391)			(0.313)
Management Fee			-0.200			-0.047
			(0.450)			(0.406)
Return			-0.001			-0.004
			(0.006)			(0.006)
Log(AUM)						0.121
						(0.142)
Year FEs	Y	Y	Y	Y	Y	Y
N	12,465	12,465	12,465	11,513	11,513	11,513